New Problem Formulation of Emission Constrained Generation Mix

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***Abstract*--This paper proposes an enhanced optimization formulation to help determine the type of power generation mix that can meet a given carbon emission target at the minimum cost. Compared to the previous studies, the model proposed in this paper takes account of the emission cost at operational level and explores its impacts on the long-term emission target oriented generation planning innovatively. Meanwhile, the model is able to take account of the integer variables and nonlinearity of the operational cost together with network constraints and renewable generation expansion in one long-term generation planning model. The problem is solved by an innovative discrete gradient search method, and a new concept, Emission Reduction Cost (ERC) is developed, which helps determine which generation technology is the most cost efficient in emission reduction during different stages of generation expansion. A case study on a modified IEEE 30 bus system is presented to demonstrate the application of this model and the value of considering short-term emission costs and the network constraints on the long-term generation expansion. The results and sensitivity analysis are provided to show that a higher short-term financial pressure can help realize the emission target at a lower total cost (investment and operational costs). Optimization without considering it may overestimate the total cost required for the generation mix restructuring. Additionally, a comparative study shows that optimization without considering network constraints may underestimate the total cost required for realizing the specified emission reduction target.**

***Index Terms*--Emission target, Generation mix, Emission cost, Network constraints, Renewable generation.**

I. Introduction

Many countries have announced ambitious carbon emission control targets. For example, the UK has committed to reduce its carbon emission by 80% by 2050, relative to 1990 levels. The power industry, the biggest carbon emitter among all industrial sectors, has to take the largest decarbonization responsibility. Hence, the ambitious long-term emission reduction target tends to drive the power system to restructure itself radically; for example, a large share of clean and renewable generation technologies will penetrate into the generation mix and investment will be required for this evolution.

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Having a comprehensive optimized generation mix as a reference would assist the policy makers in setting the emission reduction target and estimating its total cost.

A number of previous works have been carried out on the optimal generation mix problem to meet forecasted load growth. Morris innovatively employed a dynamic programming model for solving the generation mix problem [1]. Masse and Gibrat applied the linear programming (LP) to the generation investment optimization problem [2]. In [3], three different decomposition approaches were compared to tackle the generation planning problem considering the demand uncertainty. More uncertain factors, such as renewable generation intermittency, regulatory policy uncertainties and fuel price volatility were considered in [4]. In [5], the authors proposed a generation expansion planning model in deregulated environment, which was to maximize the payoff of the privatized generation companies. A generation mix optimization model considering the short-term demand side response was proposed in [6]. Bloom applied Benders' decomposition approach to dividing the generation expansion problem into master capacity optimization problem and sub operation and reliability optimization problem [7, 8]. However, these researches oversimplified the operational modeling: integer variable related costs and constraints were neglected, such as unit start-up cost, and minimum up time. Kamalinia proposed a security-constrained stochastic generation expansion model, considering the uncertainties of system component outage and forecast errors of wind and load [9]. The integer variables are both considered in expansion problem and operational problem by Benders decomposition approach in this paper. However, this paper assumed wind generation integration was given; only fast-response unit's expansion was planned. Besides, the operational cost was simplified to a linear one in the paper. These simplifications cannot better differentiate the performance (cost and flexibility) of different generation technologies. Additionally, these researches consider neither the system network constraints nor an interface for renewable generation planning. Therefore, these simplifications may bias the generation planning results. Besides, all the aforementioned studies did not consider the emission problem.

Since Gent and Lamont [10] did the early research on minimum emission dispatch, the optimization of the emission reduction has been considered more and more by successive researchers, but they mainly concentrated on the area of short-term power generation operation [11-14]. Some recent works

have been carried out in the area of emission constrained generation expansion planning. A new efficient GA-Bender's approach, solving the power generation expansion planning problems with emission constraints, was given in [15]. However, the operational problem was still modeled in the aforementioned simplified manner and did not consider renewable generation and network constraints in the optimization. In [16], the author proposed a low carbon power generation expansion model, which integrates a comprehensive set of low carbon factors. However, the whole problem was only formulated as a linear programming model. The integer characteristic of generation capacity was even ignored. The simplified linear programming model is also applied to [17, 18]. Both [15] and [16] did not explore the impacts of the short-term emission cost on the long-term optimal generation mix. Doherty made a trend analysis of the generation portfolio in Ireland, considering the impact of emission costs to the optimal generation investment portfolios [17, 18]. Unfortunately, the study only formulated the emission cost in the objective function without setting an emission target as a constraint.

In summary, most of the previous researches on optimal generation mix planning have one or more of the following limitations:

i) Integer variable cost and the nonlinearity of the operational level are neglected [3-6, 14-19]. Discrete characteristic of generation unit size in the investment level is ignored as well [16-18].
ii) There is only limited discussion of the impact of short-term emission cost on the long-term investment cost [17, 18].
iii) Network constraints and renewable generation expansion are seldom considered in the emission target oriented generation planning [15-18].

This model attempts to determine the required generation mix which can meet a predefined emission target for a given power network at a minimum societal cost, overcoming the aforementioned limitations. The contribution of this paper is that the proposed model can take account of the emission cost in operational level and reveal its impact on the long-term emission target oriented generation planning. Meanwhile, the model proposed in this paper takes into account the integer variables and the nonlinearity of operational cost with network constraints and renewable generation expansion together into one long-term generation planning model.

The model proposed in this paper is a centralized generation planning model. It aims to provide a low carbon generation mix assessment tool for policy makers when devising emission reduction targets and estimating the related cost. The government or other related authorities can use this assessment model to ensure long-term emission target could be achieved at a minimum societal cost. Since this formulation has a large problem size, due to taking into account detailed operational modeling, such as unit commitment and network constraints, an innovative index, emission reduction cost (ERC) has been developed to speed up the process of searching for the optimal generation technology. A case study based on modified IEEE 30 bus test system is provided to verify the effectiveness of this formulation. Optimization results show the total cost variation with different emission prices and targets. A comparative study has been made between optimizations with and without network constraints to indicate the importance of network constraints in a generation expansion study.

The rest of the paper is organized as follows: Section II gives the problem formulation; the solution method is presented in Section III; Section IV provides a case study to verify the effectiveness of the solution method; conclusions are drawn in Section V.

II. Problem Formulation

The developed model takes the emission target settings, current generation mix, network data and load profiles in the target year as inputs. It considers typical thermal generation units and renewable wind units, and provides the optimized generation mix and the total cost and emission under this mix as outputs. The formulation follows the way that, based on an initial generation mix, the candidate generators will be added into the mix stage by stage in a trial way. The selection of the candidate generator at a stage is based on the cost efficiency for emission reduction at that stage.

A. Operational sub problem

In order to assess the performance of a potential generation mix after introducing a candidate generator in terms of cost and carbon emission, the operational sub problem is modeled first. The operational sub-problem includes two important parts, unit commitment (UC) and economic dispatch (ED). UC determines the optimal unit combination transition path from one scheduling block to the next, while ED determines the optimal power output for each committed unit in each scheduling block.

1. Load dispatch optimization

In this research, a quadratic fuel cost function is used to better reflect the real characteristic of a generator unit. For a system with N generation units at a time horizon of T, the fuel cost ($FC_i(P_{it})$) of unit i at interval t is:

$$FC_i(P_{it}) = a_i P_{it}^2 + b_i P_{it} + c_i \quad (1)$$

where, i is the generation unit index, t is the scheduling time interval index and P_{it} is power output of unit i at interval t. a_i, b_i and c_i are the fuel cost function coefficients of unit i.

The carbon emission (E_i) of unit i at interval t is modeled linearly by:

$$E_i(P_{it}) = \beta_i P_{it} + \gamma_i \quad (2)$$

where, β_i and γ_i are the emission function coefficients of unit i.

In order to take the financial pressure of emission into account in the power dispatch [20], the emission is monetized and incorporated with the fuel cost by a weighting factor λ. The objective of the ED is to minimize the summation of fuel cost and weighted emission cost (SC_t):

$$\text{Minimize} \qquad \mathrm{SC}_t = \sum_{i=1}^{N} (FC_i(P_{it}) + \lambda E_i(P_{it})) \tag{3}$$

Subject to the following constraints:

$$P_{i\min} \le P_{it} \le P_{i\max} \qquad \forall t \in T; \tag{4}$$

$$\sum_{i=1}^{N} P_{it} = D_t \qquad \forall t \in T; \tag{5}$$

$$\sum_{i=1}^{N} sr_{it} \ge SR_t \qquad \forall t \in T; \tag{6}$$

$$SR_t = DSR \times D_t + WSR(\sum_{n=1}^{NW} P_{wn}) \quad \forall t \in T \tag{7}$$

$$-Lim_b <= L_{bt} <= Lim_b \qquad \forall b \in B, \forall t \in T \tag{8}$$

where, the weighting factor λ is the emission penalty factor, reflecting the extent of impact on the power production cost from units' carbon emissions. In practice, its forms can be emission trading price or emission tax depending on which economic scheme is implemented for emission control. In this study, emission price (EP) is uniformly used to call the factor λ in the rest of this paper. A higher emission price will exert larger pressure to emission reduction during the dispatch, and therefore power is more likely to be dispatched from clean but expensive units, vice versa. P_{imin} and P_{imax} are the minimum and maximum power output of unit i. D_t is the system total demand at the interval t. sr_{it} is the spinning reserve provided by unit i at interval t, while SR_t is the system spinning reserve requirement at interval t. SR_t at each interval is determined by two parts. DSR is a coefficient determining system spinning reserve requirement due to demand forecasting errors. *WSR* is a coefficient determining the spinning reserve requirement due to the wind power intermittency. *NW* is the number of the wind farms, and P_{wn} is the notional installed capacity of wind farm n [19]. L_{bt} is the power flow of line b at time t and Lim_b is the line flow limit of the line b.

The ED problem is solved by Lambda-Iteration method which is also known as Lagrange multiplier method [21, 22].

For dispatch result in each interval, there is an interface to conduct line flow overloading check by load flow calculation to determine if the dispatch results are static operational.

2. Unit commitment optimization

ED handles the nonlinear fuel cost, while the integer variable cost and constraints such as the unit's start-up cost, shut-down cost, unit's, minimum up time (MUT), minimum down time (MDT) and ramping rate will be dealt in UC. Dynamic programming algorithm is adopted to solve the UC optimization in this research. The UC optimization aims to minimize the aggregated operational cost (C_a) through the whole UC horizon T.

$$C_{aT} = \sum_{t=1}^{T} SC_t + \sum_{i=1}^{N}\sum_{t=1}^{T} (ST_{it} + SD_{it} + MC_{it}) \tag{9}$$

where, ST_{it} is start-up cost of unit i, SD_{it} is shut-down cost of unit i, MC_{it} is maintenance cost of unit i.

B. Generation mix optimization

The operational sub-problem in Section A essentially acts as an performance evaluator for a given generation mix, network data and load profile, evaluating the total generation costs and emissions for a desired time period.

In order to restructure the generation mix, the capacities of some generation technologies will be expanded or contracted. So, the investment cost C_c for power plant is included in the total cost C_{total}. Since the wind generation expansion is considered in this research, a high level of wind power penetration will decrease the reliability of power supply, and loss of load probability will increase, which leads to societal cost. This form of cost is taken into account through augmentation of spinning reserve requirements. The parameter, reserve price (RP) represents the price per MW spinning reserve capacity from the conventional generation plants. For a simplification, the reserve price is assumed to be equal for different conventional generation technologies. Therefore, the optimization objective is extended as well:

$$\min C_{total} = C_a + C_c + RP\sum_{t=1}^{T}\sum_{i=1}^{N} sr_{it} \tag{10}$$

$$\text{Subject to } \sum_{i=1}^{N}\sum_{t=1}^{T} E_i(P_{it}) <= E_{T\arg et} \tag{11}$$

where, E_{target} is emission limit in the target year.

In order to reduce the calculation burden and focus on the main problem, the following assumptions are made:

i) The load in the target year is assumed to be well forecasted. Since the electricity load growth in a long term is hard to be accurately forecasted, it deserves another big research based on stochastic analysis.
ii) The network topology in the target year is the same as those given in the initial state.
iii) The newly added plants are assumed to be connected to the node where the units of the same technology are located initially.
iv) No unit is retired from the initial generation mix in the target year. Because: 1) the proposed model is static, and therefore the dynamic process is neglected; 2)conventional generation capacity has to be expanded accordingly to provide backup for increased wind capacity. It offsets some units' retirement.

C. Wind power modeling

In this paper, the wind generation technology is used to stand for the renewable generation. The power output of a wind turbine can be described by (12) [19, 23]:

$$P_w = \begin{cases} P_{wr}\dfrac{v_w - v_{ci}}{v_r - v_{ci}}, & (v_{ci} < v_w < v_r) \\ 0, & (v_w < v_{ci} \ or \ v_w > v_{co}) \\ P_{wr}, & (v_r < v_w < v_{co}) \end{cases} \tag{12}$$

where, P_w is the instantaneous output of a wind turbine; P_{wr} is the rated power output of a wind turbine. v_w, v_{ci}, v_r and v_{co} are instantaneous wind speed, cut-in speed, rated speed and cut-out speed.

Wind speed probability distribution in this research is modeled by Weibull probability function.

$$f(v_w)=\frac{k}{\eta}\left(\frac{v_w}{\eta}\right)^{k-1}\cdot\exp[-(\frac{v_w}{\eta})^k] \quad (13)$$

where. k is the shaping factor and η is the scaling factor. A set of random numbers are generated following the Weibull distribution for the operation scheduling horizon by MATLAB, representing the power outputs of a wind farm in every scheduling interval. Wind farm output power is taken as negative load and used to mitigate the total power demand in each scheduling interval. In reality, even in short-term operation, wind speed still can't be forecast very accurately, let alone long-term wind speed forecast. Short-term operation scheduling and the long-term generation planning will be severely affected by the way in which the wind profile and the load profile couples each other. For example, if the wind can contribute more in peak load time, then system total fuel cost and emission could be saved and in long-term view, additional generation capacity expansion may be avoided. However, the uncertainty analysis requires a big stochastic modeling effort. This paper places its key focus on the mixed-integer nonlinear modeling of generation mix optimization problem considering short-run operational cost and emission. The uncertainty of long-term wind and demand forecast is neglected in this paper and will be considered in our later study.

III. Methodology

Notably, the model proposed is a mix-integer nonlinear programming (MINLP) problem. It is hard to be solved directly by a single optimization algorithm. This paper proposes an innovative method to tackle the problem in two stages. Dynamic programming solves the sub operational model, while a heuristic gradient search for the capacity expansion problem. The flow chart of the proposed optimization process is shown in Fig.1. It first examines the initial generation mix by conducting a UC for a horizon of T, and checks whether the resultant emission meets the target or not. If yes, that means the current generation mix can already meet the emission target, otherwise, the optimization begins.

The relation of the cost and emission performance with a generation mix can be represented as follows:

$$C_{total}=f(P_1,P_2,.....,P_n) \quad (14)$$

$$E_{total}=g(P_1,P_2,.....,P_n) \quad (15)$$

In order to speed up the search for optimal generation mix, a new term named Emission Reduction Cost (ERC) is defined to represent the ratio between the cost increase due to a candidate generator introduction and the resultant emission reduction, given by the following numerical differentiation:

$$ERC\big|_{\Delta P_n}=\frac{\Delta C_{total}\big|_{\Delta P_n}}{\Delta E_{total}\big|_{\Delta P_n}}=\frac{f(P_1,P_2,...,P_n+\Delta P_n)-f(P_1,P_2,...,P_n)}{g(P_1,P_2,...,P_n+\Delta P_n)-g(P_1,P_2,...,P_n)} \quad (16)$$

The search is essentially based on gradient search using ERC as the goodness index. Based on an initial generation mix, assuming M units are added to form the final optimal mix, which meets the emission target, the optimization will be divided into M cycles. In each cycle, denoted by m, the program will add one unit ΔP from each candidate generation technology respectively to evaluate the ERCs under different expanding strategies. The unit whose technology has the lowest ERC will be chosen to add into the generation mix for the m^{th} cycle. The decision making for the next cycle, the $(m+1)^{th}$ cycle, will be repeated based on the optimal mix determined by the m^{th} cycle. The process will iterate M times until no further optimal mix can be found.

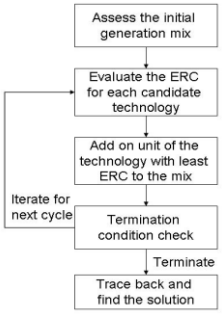

Fig. 1. Flow chart of the generation mix optimization algorithm

$$ERC_m=\begin{bmatrix} ERC_m\big|_{\Delta P_1} \\ ERC_m\big|_{\Delta P_2} \\ \cdots \\ ERC_m\big|_{\Delta P_n} \end{bmatrix}=\begin{bmatrix} \frac{f_m(P_1+\Delta P_1,P_2,...,P_n)-f_{m-1}(P_1,P_2,...,P_n)}{g_m(P_1+\Delta P_1,P_2,...,P_n)-g_{m-1}(P_1,P_2,...,P_n)} \\ \frac{f_m(P_1,P_2+\Delta P_2,...,P_n)-f_{m-1}(P_1,P_2,...,P_n)}{g_m(P_1,P_2+\Delta P_2,...,P_n)-g_{m-1}(P_1,P_2,...,P_n)} \\ \cdots \\ \frac{f_m(P_1,P_2,...,P_n+\Delta P_n)-f_{m-1}(P_1,P_2,...,P_n)}{g_m(P_1,P_2,...,P_n+\Delta P_n)-g_{m-1}(P_1,P_2,...,P_n)} \end{bmatrix} \quad (17)$$

The terminating criteria for the iteration are:In the m^{th} cycle, after evaluating the ERCs of N technologies, record the candidate technologies which meet the emission target into a set S. From the set, only the technology with the least ERC is added into the generation mix, and move on to the next cycle;

ii) In the final cycle, after evaluating the ERCs of N technologies, if E_{total} from all N technologies are below the emission target, terminate the iteration and trace back to find the solution with the least C_{total} from the set S.

It should be noted that ERCs for the same technology may vary in different cycles. This is because generation mixes at different cycles are different, resulting in different impacts on the costs and emissions from the same technology intervention.

In operational sub-problem, (6) indicates the system minimum spinning reserve requirement. Thus, before each iteration, there is a conventional capacity margin check to see is a new wind unit can be added into the mix. If, after the new wind unit is added, the total conventional capacity can not afford the peak demand plus the peak reserve requirement as (18) indicates, the wind capacity expansion will be forgone for this cycle.

$$Conventional\ Capacity < D_{peak}+DSR\times D_{peak}+WSR(\sum_{n=1}^{NW}P_{wn}) \quad (18)$$

IV. Case Study

A case study is presented in this section to demonstrate the application of the proposed model. Sensitivity analysis is conducted to show the importance of considering short-term emission cost in generation mix optimization. Comparative

study between optimizations with and without network constraints is made to show the importance of considering network constraints in a generation expansion study.

TABLE I
GENERATOR DATA PART 1

Technologies	a (£/(MW)^2)	b (£/MW)	c (£)	β (ton/MW)	γ (ton)	Cc (£/MW)
CCGT[1]1	0.024	6	300	0.38	0.03	483760
CCGT2	0.022	6.4	296	0.39	0.02	481880
COAl PF[2]1	0.032	4.06	630	0.84	0.03	1109175
COAl PF2	0.035	3.64	595	0.82	0.04	1101075
IGCC[3]1	0.014	4.06	756	0.6	0.02	1585200
IGCC2	0.017	3.78	777	0.62	0.01	1573200
OGCT[4]1	0.03	5	706	0.47	0.02	466580
OGCT2	0.034	4.6	720	0.45	0.04	465380
WIND1	0	0	0	0	0	885041
WIND2	0	0	0	0	0	886340

TABLE II
GENERATOR DATA PART 2

Technologies	Notional capacity (MW)	Pmin (MW)	Pmax (MW)	Bus No.	Initial Units installed
CCGT1	300	100	300	11	1
CCGT2	350	100	350	5	1
COAl PF1	300	100	600	2	2
COAl PF2	300	50	300	1	1
IGCC1	200	80	400	19	2
IGCC2	250	10	250	14	1
OGCT1	100	20	200	8	2
OGCT2	150	50	300	13	2
WIND1	50	0	150	27	3
WIND2	40	0	200	24	5

A. *Test input*

An IEEE 30 bus test system was adopted in this research, which is shown in Fig.2. There are comparative studies subsequently between the cases of whether or not considering network constraints. For the case of considering the network constraints, the thermal ratings of all 41 transmission lines are set to 100MW evenly. For the other case, the thermal ratings are set to infinite. Of the 20 units connected to the grid, there are 10 different generation technologies, of which 8 technologies are conventional fossil fuel fired power plants with different performance on fuel cost, emission, and capital cost, and the others are 2 different wind farms which have zero fuel cost and emission output. The details of the 10 generation technologies are given in Table I and Table II. The wind turbines' speed parameters are assumed to be the same, as v_{ci} = 5*m/s*, v_{co}=45*m/s*, and v_r=15*m/s*.. Since the turbines have been connected to two different locations, the wind speed Weibull distribution parameters for the two locations are differentiated. They are η =10.2, k=1.5 for WIND1, and η=8.6, k=1.5 for WIND2. These parameters are set to give a capacity factor of around 40% for WIND1 and 30% for WIND2. The load profile in this research is derived according to the IEEE Reliability Test System 1996 with a total demand of annual aggregated peak demand of 2830 MW scaled base on the demand data provided in the IEEE 30 bus test system [24]. The hourly load is determined by the multiplication of annual peak demand and the coefficients of weekly peak demand in percentage of the annual peak, daily peak demand in percentage of the week peak and hourly peak demand in percentage of the daily peak. Although this model allows any long planning horizon, in order to reduce the calculation burden, this research only takes four days as the samples to estimate the yearly total operation cost. The four days are the first day of each season. The DSR and WSR are set to 5% and 80%, and the reserve price (RP) is assumed to be 5 £/MW/h. A sensitive analysis is provided to investigate the impacts of different emission prices (λ) on the generation planning.

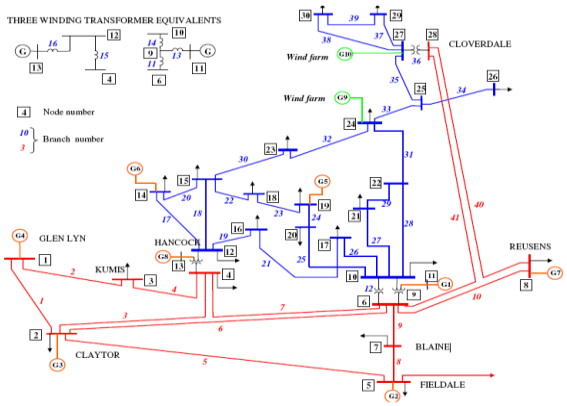

Fig.2. IEEE 30 bus test system [25]

TABLE III
EMISSION REDUCTION TARGET SCENARIOS

Reduction percentage	Reduction Target (ton)			
	EP=5	EP=10	EP=20	EP=30
current	8.95E+06	8.85E+06	8.67E+06	8.51E+06
9.9%	8.06E+06	7.98E+06	7.81E+06	7.67E+06
14.2%	7.68E+06	7.68E+06	7.44E+06	7.30E+06
18.5%	7.29E+06	7.29E+06	7.07E+06	6.93E+06
22.8%	6.91E+06	6.91E+06	6.69E+06	6.57E+06

B. *Methodology implementation*

The relationship between emission target and the corresponding optimized generation mix and its year-round performance in terms of total cost and emission is investigated. Based on the emission of the current generation mix, 4 emission reduction targets are assumed for 4 different emission prices in the current and target year. The 16 scenarios are listed in Table III. Because the emission price can influence the emission results, in order to illustrate the emission reduction achieved entirely by restructuring the generation mix, it is assumed that the target year and current year have the same emission price for all scenarios. For the 16 scenarios, 16 optimal generation mixes have been found that meet the different levels of emission target. The generation mixes under various targets are shown in Fig.3 and the corresponding total

1 CCGT: combined cycle gas turbine generation technology
2 COAL PF: pulverized fuel coal fired generation technology
3 IGCC: integrated gasification combined cycle generation technology
4 OGCC: open cycle gas turbine generation technology

cost and emission for each optimized generation mix are listed in Table IV and depicted in Fig.4.

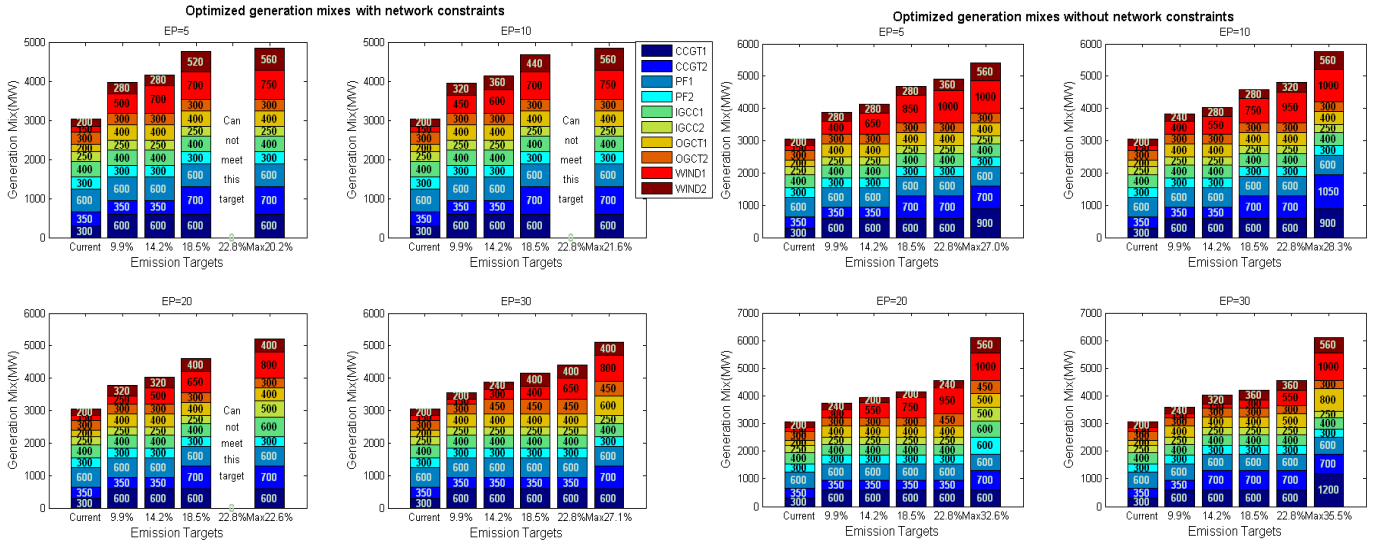

Fig.3. Optimized generation mixes under different emission target settings with and without network constraints

TABLE IV
COST AND EMISSION RESULTS OF OPTIMIZATION WITH NETWORK CONSTRAINTS

Reduction percentage	Total cost (£)				Total emission (ton)			
	EP=5	EP=10	EP=20	EP=30	EP=5	EP=10	EP=20	EP=30
current	*3.14E+09*	3.19E+09	3.27E+09	3.36E+09	8.95E+06	8.85E+06	8.67E+06	8.51E+06
9.9%	3.76E+09	3.79E+09	3.69E+09	*3.58E+09*	8.04E+06	7.95E+06	7.77E+06	7.65E+06
14.2%	3.93E+09	3.95E+09	3.90E+09	*3.81E+09*	7.66E+06	7.59E+06	7.39E+06	7.28E+06
18.5%	4.31E+09	4.27E+09	4.27E+09	*4.03E+09*	7.25E+06	7.16E+06	6.96E+06	6.92E+06
22.8%	N/A	N/A	N/A	4.23E+09	N/A	N/A	N/A	6.52E+06

TABLE V
COST AND EMISSION RESULTS OF OPTIMIZATION WITHOUT NETWORK CONSTRAINTS

Reduction percentage	Total cost (£)				Total emission (ton)			
	EP=5	EP=10	EP=20	EP=30	EP=5	EP=10	EP=20	EP=30
current	3.14E+09	3.19E+09	3.27E+09	3.36E+09	8.95E+06	8.85E+06	8.67E+06	8.51E+06
9.9%	3.66E+09	3.67E+09	3.66E+09	3.51E+09	8.01E+06	7.89E+06	7.77E+06	7.64E+06
14.2%	3.88E+09	3.83E+09	3.84E+09	3.75E+09	7.63E+06	7.58E+06	7.32E+06	7.28E+06
18.5%	4.22E+09	4.17E+09	4.01E+09	4.00E+09	7.25E+06	7.16E+06	6.92E+06	6.92E+06
22.8%	4.42E+09	4.38E+09	4.28E+09	4.16E+09	6.87E+06	6.79E+06	6.64E+06	6.57E+06

In order to reflect the difference between optimizations with and without considering network constraints, the same evaluation has been made without considering the network constraints and the resultant generation mixes are shown in Fig.3 and the corresponding total cost and emission for each optimized generation mix are listed in Table V and depicted in Fig.5.

C. Results and discussion

The left-hand half of Fig.3 shows optimal generation mix results under 16 scenarios considering the network constraints. There are 4 stack bar charts categorized by the four different emission prices, 5, 10, 20 and 30. Each bar chart has 5 to 6 stack bars. The first and last bars are the initial generation mix and the optimal generation mix which can realize the maximum emission reduction target respectively. Each stack bar has 10 components, representing the capacities of the 10 generation technologies in the generation mix. It can be seen that for the same reduction target, the resulting optimal generation mixes are different with different emission prices. Moreover, if emission prices in target year are £5/ton, £10/ton and £20/ton, there will be no generation mixes which can meet the 22.8% reduction target. Additionally, the maximum reduction that could be achieved by restructuring the generation mix increases with the rise of emission price. For example, when the emission price is set at £5/ton, the maximum emission reduction is around 20.0%, but when the emission price rises to £30/ton, the maximum emission reduction can reach 27.1%. Therefore, there is a reduction limitation. Finally, it is important to note that the least cost to meet the more stringent emission target can only be achieved by a combination of long-term generation expansion and short-term emission control, as shown by the italic cost figures in Table IV.

The same calculation has been made without considering network constraints. The generation mix optimization results are shown in the right-hand half of Fig.3 and the corresponding cost and emission results are listed in Table V.

It can be seen that after removing these constraints, the 22.8% reduction target can be realized even for those modest emission prices, £5/ton, £10/ton and £20/ton, which previously are not able to achieve the targets. Besides, the maximum reduction could be achieved rises to 27%, 28.3%, 32.6% and 35.5% for the emission price equal to £5/ton, £10/ton, £20/ton and £30/ton respectively. Compared to the situation with those constraints, the optimization without them can reduce more emission.

It can be seen from Fig.3 that in both cases with and without network constraints, total installed capacity always increases with rising emission reduction target, although the system total demand stays the same. This is because in order to realize more stringent emission targets, more wind capacity will be expanded. An increase in the clean wind capacity will require an increase of conventional generation capacity to provide the security backups. The ratio of the two is constrained by Equation (18).

Effect of network constraints

From Table IV-V, and Fig 4-5, it can be found that in order to reach the same emission reduction target, the optimization with network constraints always realizes the target at higher or equal total cost compared to the one without network constraints. Besides, the optimization with network constraints can not reach 22.8% emission reduction target when emission price is set to £5/ton, £10/ton, and £20/ton, while it can be reached in the same cases of the optimization without network constraints. The cost differences in percentage between the optimization with and without network constraints are listed in Table VI. The differences vary from 0.74% to 6.09%, while the biggest difference is the optimization with constraints which could not achieve the 22.8% reduction target when emission price is equal to £5/ton, £10/ton, and £20/ton. This shows the importance of taking network constraints into account to avoid underestimating the cost for generation investment.

Effect of emission price

From Fig.4-5, it can be observed clearly that with emission target becoming stricter, the total emission drops almost at the same rate for different emission price cases, while the total cost is rising at different rates of change. Generally for the same emission reduction target, a higher emission price can help find the optimal mix to meet the target at a lower total cost. This is because a higher emission price can make the clean technologies more cost efficient during the expansion process. It can avoid the capacity expansion from the technologies that are less clean but expensive. Thus, the large capital cost could be saved. This shows the importance of considering the short-term financial pressure at the generation expansion planning.

Emission reduction limit

For a fixed amount of demand, the system's total emission can not be reduced as much as desired merely by increasing the clean units' penetration. It has a reduction limit. If the network constraints are considered, the limit will be much tighter. That is because although the wind energy is modeled as a zero emission generation source, the rise of wind energy penetration has to rely on an increase of conventional generation capacity to provide sufficient spinning reserve to compensate the intermittency. Meanwhile, the conventional power plants are constrained to run at a minimum power output once they are started up for providing the spinning reserve. Their minimum power output causes a certain amount of emission which is the aforementioned emission reduction limit. Only when the technologies are improved to diminish the constraints of the current generation and operation technologies, could the emission be further reduced.

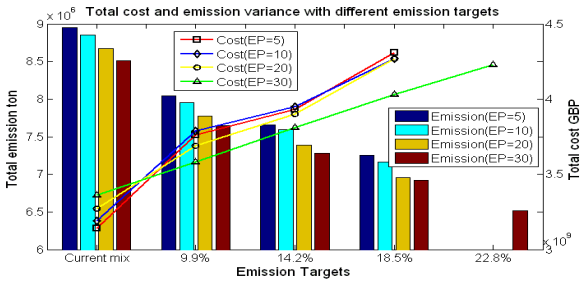

Fig.4. Cost and emission results with network constraints

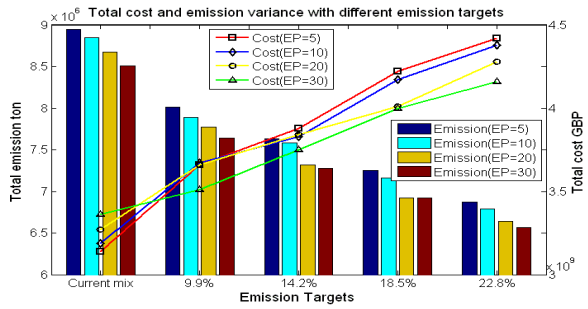

Fig.5. Cost and emission results without network constraints

TABLE VI
COST DIFFERENCE BETWEEN OPTIMIZATIONS WITH AND WITHOUT NETWORK COSNTRAINTS

Reduction percentage	Total cost difference (£)			
	EP=5	EP=10	EP=20	EP=30
9.90%	2.66%	3.17%	0.81%	1.96%
14.20%	1.27%	3.04%	1.54%	1.57%
18.50%	2.09%	2.34%	6.09%	0.74%
22.80%	N/A	N/A	N/A	1.65%

The case study has presented the application of this model under 16 different scenarios with different emission reduction targets ranging from 9.9% to 22.8% combined with different emission charge prices ranging from 5 £/ton to 30£/ton. It can be found that a more stringent emission target can be achieved more economically by a combination of long-run generation expansion and short-run emission control. The results also indicate a higher emission price can help find the optimal mix to meet the target at a lower total cost. They show the importance of including the emission financial pressure when optimizing the generation investment. Optimizations are

conducted both with and without network constraints under the 16 scenarios. The comparison between the two optimizations indicates in order to reach the same emission reduction target, the optimization with network constraints always realizes the target at higher or equal total cost compared to the optimization without network constraints. The final cost differences between the two cases vary from 0.74% to 6.09%. It shows the importance of taking network constraints into account in generation planning to avoid underestimating the cost. Besides, ignoring network constraints will make the realization of emission targets more possible than it should be. It is also found that the system total emission can not be reduced as much as expected by merely increasing the clean units' penetration. It is due to the necessity of increasing conventional generation capacity to compensate the rise of the wind generation penetration and the minimum output constraints of the conventional power plants.

V. Conclusions

This paper proposes a new generation expansion planning model, which takes account of the emission cost in operational level and explores its impacts on the long-term emission target oriented generation planning. Meanwhile, the model proposed in this paper takes into account the integer variables and nonlinearity of the operational cost with network constraints and renewable generation expansion together in a single generation planning model. The new concept Emission Reduction Cost is introduced in the generation expansion phase, which acts as a goodness index to select the most cost effective generation technologies to be expanded. The case study explores the impacts of the short-term emission cost on long-term generation planning. It also demonstrates the importance of including network constraints in the generation planning. Overall, this paper presents a centralized assessment model to find the most economical generation mix pattern in order to meet a predefined emission target, which can assist policy makers in devising the emission reduction target and estimating the related cost.

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