

Market-Based Generation Planning with Carbon Target

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Abstract—In the era of the deregulated electricity market, the necessity and urgency for reducing carbon emissions are broadly recognized, which further drives the market-based generation planning towards a low-carbon transition. In this context, this paper proposes a multi-period bi-level optimization problem, where the upper-level problem indicates the generation company pursuing maximized profit and the lower-level problem depicts the market clearing process with carbon limitations. To solve it, this bi-level optimization problem is first replaced with its mathematical program with equilibrium constraints (MPEC) model and then transformed into a mixed integer linear program (MILP) with Karush-Kuhn-Tucker (KKT) optimality conditions and strong duality theory. Case studies are carried out to evaluate the impact of carbon targets on market-based generation investment decisions and business cases.

Index Terms—Bi-level optimization, Carbon target, Electricity markets, Generation planning.

I. INTRODUCTION

Significant efforts have been made for the pathway of transition to a deep decarbonized power system in the era of deregulated electricity market with the increasing penetration of renewable energy sources (RESs). In light of the pledges of global countries for decarbonization, it is necessary to efficiently pave the way towards the carbon-neutral target by 2050 [1]. In order to achieve the urgent target of carbon neutrality, one effective approach is to eliminate heavy-polluting technologies and fossil energy sources by replacing them with alternative zero-carbon generation technologies, including nuclear, hydro-power, wind, solar, etc. In Europe, the share of electrical power generated from zero-carbon technologies has exceeded 28.2% in Germany, 38.7% in Spain, and 48.5% in Denmark [2]. Now, the UK is also revolutionizing its power system, expanding zero-carbon power technologies accounting for 50% of the generation mix [3]. However, the carbon emissions from fossil fuels in the power supply sector of the UK still hold 80.7 MtCO₂ [3]. To this end, it is still urgent to propose a new market mechanism for generation planning to accelerate the decarbonization of future power systems.

In recent years, numerous works have promoted research on generation planning problems, which can be classified into two categories: centralized planning and market-based planning. In the first category, authors in [4] investigate a

centralized generation planning problem through the distributionally robust chance-constrained program accounting for both long-term and short-term uncertainties. Authors in [5] propose a centralized investment model involving unit commitment constraints and carbon limitations in the low-carbon context. Authors in [6, 7] incorporate different carbon emissions constraints into centralized generation planning problems to find the optimal mix of investments. However, all of the centralized planning problems [4, 5, 6, 7] ignore the influence of market clearing solutions, and therefore cannot evaluate the profitability of the market-based investment decisions. In the second category, the bi-level optimization problem is proposed to formulate the market-based generation planning problem. Specifically, the upper-level (UL) problem optimizes the investment decisions of generation companies (GenCos), and the lower-level (LL) problem represents the market clearing algorithm. Authors in [8, 9] investigate the optimal investment decision of a strategic producer through the bi-level optimization problem in consideration of future markets. Authors in [10] propose a bi-level optimization problem for generation planning to assess the impact of demand flexibility. Authors in [11, 12] establish a novel bi-level optimization problem to optimize investment decisions with the considerations of both renewable energy credits and electricity markets. In [13], the generation planning with the uncertainty pertaining to wind power correlation is modelled through a bi-level optimization problem to determine optimal investment decisions. Authors in [14] develop a bi-level optimization model to solve the generation planning problem with topology control operations. Authors in [15] present a bi-level optimization model to capture generation planning and retirement decisions in simultaneously cleared capacity, energy, and reserve markets. Nevertheless, the carbon emission effect through a market-based generation planning problem has not been explored yet.

This paper aims to fill this knowledge gap by incorporating the carbon emission constraints into a bi-level optimization problem for generation planning. The main contributions are three-fold:

- 1) A novel framework of generation planning problem is proposed through a multi-period bi-level optimization problem, where the UL problem represents the

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investment decisions of GenCo and the LL problem represents the market clearing algorithm. The carbon target constraint is incorporated into this generation planning problem, aims to achieve a profit-driven and low-carbon investment decision strategy. To our best knowledge, it is the first time to investigate a market-based generation planning problem to find the optimal investment decisions for various generation technologies under the background of decarbonization.

- 2) The solution approach is applied to convert the bi-level optimization problem to a mathematical program with equilibrium constraints (MPEC) problem and subsequently, it is recast to a mixed-integer linear program (MILP), and finally can be solvable to the global optimality through commercial solvers.
- 3) A collection of case studies is designed to quantitatively analyze the impact of carbon targets on the optimal investment decisions, the market outcomes, as well as the profits of GenCos.

The remainder of this paper is organized as follows. Section II details the formulation of the proposed bi-level optimization model and the solutions of MPEC and MILP. The case studies are carried out in section III. Finally, section IV provides the conclusions of this work.

II. BI-LEVEL OPTIMIZATION PROBLEM AND SOLUTION

The proposed model is formulated as a multi-period bi-level optimization problem to capture the interactions between a self-interested GenCO (formulated in the UL problem) and the market clearing process (formulated in the LL problem), as depicted in Figure 1, left side. It can be observed that the UL and LL problems are coupled, since the investment decisions made at the UL problem affect the market outcomes cleared in the LL problem; the energy prices and power dispatches derived from the LL problem determine the profitability of the examined GenCO as well as its business cases in the UL problem.

The adopted electricity market is a pool-based and energy-only market with an hourly time resolution [16]. The time horizon is one year captured by a representative day. In contrast to unrealistic “greenfield” assumptions, the adopted market clearing algorithm includes both existing and new-invested generation units [10]. During the market clearing process, each GenCo submits its individual bids with actual marginal energy costs.

To solve this bi-level optimization problem, the LL market clearing problem is replaced by its equivalent Karush-Kuhn-Tucker (KKT) optimality conditions, subjected to the UL investment decision problem, then transformed into a single-level MPEC problem. Finally, the non-linear terms of complementary conditions and the bi-linear objective function are linearized, rendering the MPEC problem into a MILP, as depicted in Figure 1, right side.

A. Formulations of Bi-level Optimization Problem

Considering that the examined GenCo participates in the electricity market with carbon targets, the proposed bi-level

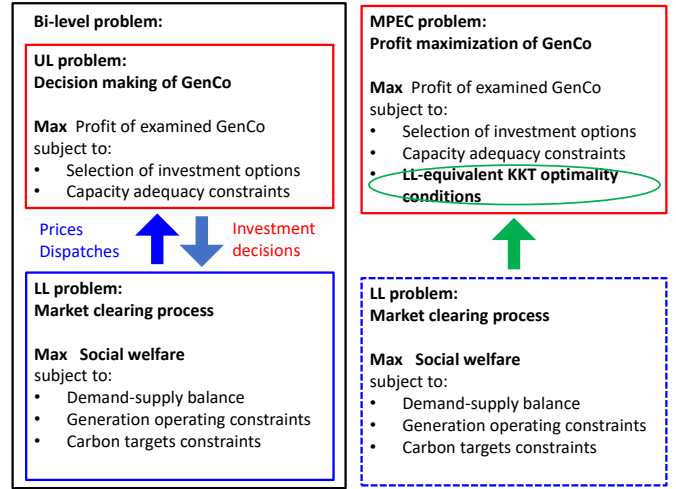


Fig. 1: Illustration and solution of the proposed bi-level optimization problem.

optimization problem can be formulated as follows:

1) UL Investment Decision Problem:

$$\begin{aligned} \max_{\{G_i, G_k, R_q\}} \omega & \left[\sum_{i,t} (\lambda_t - C_i^{EN}) g_{i,t} + \right. \\ & \left. \sum_{k,t} (\lambda_t - C_k^{EN}) g_{k,t} + \sum_{q,t} \lambda_t r_{q,t} \right] - \\ & \sum_i C_i^{IN} G_i - \sum_k C_k^{IN} G_k - \sum_q C_q^{IN} R_q \end{aligned} \quad (1)$$

subject to:

$$G_i = \sum_b N_{i,b} X_{i,b}, \forall i \quad (2)$$

$$G_k = \sum_b N_{k,b} X_{k,b}, \forall k \quad (3)$$

$$R_q = \sum_b N_{q,b} X_{q,b}, \forall q \quad (4)$$

$$\sum_i G_i + \sum_{i'} G_{i'} + \sum_k G_k + \sum_{k'} G_{k'} \geq A^S L_t, \forall t \quad (5)$$

The objective function (1) of the UL problem is maximizing the profit of the examined GenCo across the yearly horizon, which consists of (i) the energy profits of flexible technologies i and must-run technologies k (first two terms); (ii) the revenue of renewable generation technologies q (third term); and the investment costs of all generation technologies (last three terms). Since the static model is designed for investment and operation in a single target year with an hourly resolution, the typical day is weighted by factor ω , and the hourly time is denoted by subscript t . The UL decision variables consist of total invested capacities of flexible, must-run, and renewable generation technologies represented by G_i , G_k , and R_q , respectively.

The UL investment decision problem is subjected to the investment decision-making constraints of flexible, must-run, and renewable generation technologies (2)-(4), where the parameters of $X_{i,b}$, $X_{k,b}$, and $X_{q,b}$ indicate the investment option b (e.g., 30 MW and 100 MW) for flexible technology i ,

must-run technology k , and renewable generation technology q , respectively. The integer variables $N_{i,b}$, $N_{k,b}$, and $N_{q,b}$ correspond to their individual invested numbers. Finally, the regulatory constraint (5) of out-of-market adequacy is imposed on the studied GenCo by the system operator, which aims to guarantee that sufficient conventional generation capacity will satisfy the overall system demand L_t scaled by system adequacy coefficient A^S [10].

2) LL Market Clearing Problem:

$$\min_{V^{LL}} \sum_{i,t} C_i^{EN} g_{i,t} + \sum_{i',t} C_{i'}^{EN} g_{i',t} + \sum_{k,t} C_k^{EN} g_{k,t} + \sum_{k',t} C_{k'}^{EN} g_{k',t} \quad (6)$$

where

$$V^{LL} = \{g_{i,t}, g_{i',t}, g_{k,t}, g_{k',t}, r_{q,t}, r_{q',t}\} \quad (7)$$

subject to:

$$L_t - \sum_i g_{i,t} - \sum_{i'} g_{i',t} - \sum_k g_{k,t} - \sum_{k'} g_{k',t} - \sum_q r_{q,t} - \sum_{q'} r_{q',t} = 0 : \lambda_t, \forall t \quad (8)$$

$$\omega \sum_{i,t} \eta_i^{CO_2} g_{i,t} \leq E^{CO_2} : \rho \quad (9)$$

$$\omega \sum_{i',t} \eta_{i'}^{CO_2} g_{i',t} \leq E^{CO_2'} : \rho' \quad (10)$$

$$0 \leq g_{i,t} \leq G_i : \mu_{i,t}^-, \mu_{i,t}^+, \forall i, \forall t \quad (11)$$

$$0 \leq g_{i',t} \leq G_{i'} : \mu_{i',t}^-, \mu_{i',t}^+, \forall i', \forall t \quad (12)$$

$$g_{k,t} = G_k : \gamma_{k,t}, \forall k, \forall t \quad (13)$$

$$g_{k',t} = G_{k'} : \gamma_{k',t}, \forall k', \forall t \quad (14)$$

$$0 \leq r_{q,t} \leq k_{q,t} R_q : \theta_{q,t}^-, \theta_{q,t}^+, \forall q, \forall t \quad (15)$$

$$0 \leq r_{q',t} \leq k_{q',t} R_{q'} : \theta_{q',t}^-, \theta_{q',t}^+, \forall q', \forall t \quad (16)$$

The objective function (6) of the LL problem is minimizing the total generation cost of the market, consisting of existing and new-invested generation units of both flexible and must-run technologies, where the parameter of C^{EN} represents their marginal cost. The indexes i, k, q and i', k', q' indicate the units of new-invested and existing generation, respectively. It is assumed that renewable generation technologies have zero marginal cost. The decision variables of the LL problem are composed of power dispatches $g_{i,t}, g_{k,t}, r_{q,t}, g_{i',t}, g_{k',t}, r_{q',t}$, respectively.

The LL problem is subjected to the system demand-supply balance constraint (8), where the dual variables constitute market clearing prices λ_t . In the sight of decarbonization, which is the focus of this work, constraints (9) and (10) exert the system-wide carbon targets, E^{CO_2} and $E^{CO_2'}$, on the new-invested and existing flexible generation units, respectively. Furthermore, it is assumed that carbon emissions only depend on carbon intensities $\eta_i^{CO_2}$ and $\eta_{i'}^{CO_2}$, as well as

power dispatches $g_{i,t}$ and $g_{i',t}$. Constraints (11) and (12) express the dispatch limits of flexible generation technologies. Equations (13) and (14) enforce that must-run generation technologies have to operate at their full capacities all the time. Finally, constraints (15) and (16) express the dispatch limits of renewable generation technologies by the products of their power capacities and the normalized forecasting parameters $k_{q,t}, k_{q',t}$.

B. Solution of Bi-level Optimization Problem

In consideration of the continuity and convexity of the LL problem, it can be substituted by its KKT optimality conditions. In this context, the proposed bi-level optimization problem (1)-(16) can be transformed into a single-level MPEC problem in order to solve it efficiently. Specifically, the main steps of its transformation are outlined for the sake of clarity and completeness:

Step 1: The objective function of MPEC is consistent with the equation (1). Furthermore, the constraints of UL problem (2)-(5) are also retained as part of MPEC's constraints.

Step 2: The next step is to convert the LL problem into its equivalent KKT optimality conditions, which firstly includes its original equality constraints (8), (13) and (14);

Step 3: Additionally includes the KKT stationarity conditions (17)-(22), which are derived from the first-order partial differentials of the Lagrangian function of the LL problem with respect to its variable set V^{LL} in (7);

Step 4: Finally includes the KKT complementarity slackness conditions (23)-(32), which exhibit the complementary relationship between inequality constraints and the associated Lagrangian multipliers.

$$C_i^{EN} - \lambda_t + \omega \eta_i^{CO_2} \rho + \mu_{i,t}^+ - \mu_{i,t}^- = 0 \quad \forall i, \forall t \quad (17)$$

$$C_{i'}^{EN} - \lambda_t + \omega \eta_{i'}^{CO_2} \rho' + \mu_{i',t}^+ - \mu_{i',t}^- = 0 \quad \forall i', \forall t \quad (18)$$

$$C_k^{EN} - \lambda_t + \gamma_{k,t} = 0 \quad \forall k, \forall t \quad (19)$$

$$C_{k'}^{EN} - \lambda_t + \gamma_{k',t} = 0 \quad \forall k', \forall t \quad (20)$$

$$-\lambda_t + \theta_{q,t}^+ - \theta_{q,t}^- = 0 \quad \forall q, \forall t \quad (21)$$

$$-\lambda_t + \theta_{q',t}^+ - \theta_{q',t}^- = 0 \quad \forall q', \forall t \quad (22)$$

$$0 \leq E^{CO_2} - \omega \sum_{i,t} \eta_i^{CO_2} g_{i,t} \perp \rho \geq 0 \quad (23)$$

$$0 \leq E^{CO_2'} - \omega \sum_{i',t} \eta_{i'}^{CO_2} g_{i',t} \perp \rho' \geq 0 \quad (24)$$

$$0 \leq g_{i,t} \perp \mu_{i,t}^- \geq 0 \quad \forall i, \forall t \quad (25)$$

$$0 \leq g_{i',t} \perp \mu_{i',t}^- \geq 0 \quad \forall i', \forall t \quad (26)$$

$$0 \leq G_{i,n} - g_{i,t} \perp \mu_{i,t}^+ \geq 0 \quad \forall i, \forall t \quad (27)$$

$$0 \leq G_{i'} - g_{i',t} \perp \mu_{i',t}^+ \geq 0 \quad \forall i', \forall t \quad (28)$$

$$0 \leq r_{q,t} \perp \theta_{q,t}^- \geq 0 \quad \forall q, \forall t \quad (29)$$

$$0 \leq k_{q,t} R_q - r_{q,t} \perp \theta_{q,t}^+ \geq 0 \quad \forall q, \forall t \quad (30)$$

$$0 \leq r_{q',t} \perp \theta_{q',t}^- \geq 0 \quad \forall q', \forall t \quad (31)$$

$$0 \leq k_{q',t} R_{q'} - r_{q',t} \perp \theta_{q',t}^+ \geq 0 \quad \forall q', \forall t \quad (32)$$

C. Linearization of MPEC

The MPEC formulation is characterized by two-fold non-linearities: i) KKT complementarity slackness conditions and ii) bilinear terms in the objective function (1), which are the products of market clearing prices and power dispatches. Since the global optimality cannot be guaranteed in the presence of non-linearities, the MPEC proposed above is converted to a MILP, which can be efficiently solved using commercial branch-and-cut solvers.

In order to find the linearized expressions of KKT complementary slackness conditions, the linearization method provided by [16], namely the big-M method, is implemented in this model. Generally, KKT complementarity slackness conditions in the above MPEC can be expressed as $0 \leq a \perp b \geq 0$, where a and b represent the primal variable and corresponding dual variable respectively. In respect of linearization, each complementarity slackness condition can be replaced by a mixed integer constraint set $\{a \geq 0, b \geq 0, a \leq \beta M^a, b \leq (1 - \beta) M^b, \beta \in \{0, 1\}\}$, where M^a and M^b are large enough constants. Specifically, β is the auxiliary binary variable.

For the sake of eliminating non-linearities existing in the objective function, the linearization technique proposed in [8] is adopted in this work, which exploits the strong duality theorem and a portion of equalities of KKT optimality conditions to substitute the bilinear terms in the objective function with linearized expressions. For brevity, details of transformation are not presented here, but its final expression is written as:

$$\begin{aligned} & \omega \left[- \sum_{i,t} C_i^{EN} g_{i,t} - \sum_{i',t} C_{i'}^{EN} g_{i'0,t} - \sum_{k,t} C_k^{EN} g_{k,t} \right. \\ & - \sum_{k',t} C_{k'}^{EN} g_{k',t} + \sum_t L_t \lambda_t - E^{CO_2} \rho' - \\ & \left. \sum_{i',t} G_{i'} \mu_{i',t}^+ - \sum_{k',t} G_{k'} \gamma_{k',t} - \sum_{q',t} k_{q',t} R_{q'} \theta_{q',t}^+ \right] - \\ & \sum_i C_i^{IN} G_i - \sum_k C_k^{IN} G_k - \sum_q C_q^{IN} R_q \end{aligned} \quad (33)$$

III. CASE STUDIES

A. Data and Implementation

In light of the computational burden, the evaluated market horizon is one year with an hourly resolution, i.e., $T = \{1, 2, \dots, 24\}$. In order to simplify the optimization, a representative day is selected to capture the demand characteristics, weighted by 365 days (i.e., $\omega = 365$) to express the yearly demand profiles. The energy supply is supported by four types of technologies, namely combined cycle gas turbines (CCGT), open cycle gas turbines (OCGT), nuclear power, and wind turbines (WTs), respectively. Specifically, in order to be consistent with the classifications of technologies employed by modelling, CCGT and OCGT constitute

flexible generation, nuclear power is considered as the must-run generation, and WT is the form of renewable generation. An illustrative power system with seven existing installed generation units (including 2 CCGT, 2 OCGT, 2 WT, and 1 nuclear) is utilized for the generation planning model. For brevity, the comprehensive parameters of investment options, existing generators, baseline demand, and normalized wind forecasting are collected from [10]. Finally, the carbon intensities of CCGT and OCGT are obtained from [5], and it is noted that nuclear and WT are carbon-free technologies.

As aforementioned, the overarching scope of this work is to reveal the effect of various degrees of carbon targets on generation investment decisions towards a net-zero transition. In this context, three different cases regarding carbon targets are analyzed in investment decisions:

- 1) *High-carbon (HC)*: Carbon target is not applied to investment decisions, which constitutes the benchmark.
- 2) *Low-carbon (LC)*: The carbon target for invested generation units is capped at 50 tonnes.
- 3) *Zero-carbon (ZC)*: The carbon target for invested generation units is restricted to zero.

The quantitative analysis of case studies is implemented in the developed MILP model and subsequently conducted using Gurobi 10.0 under Python 3.10 integrated with Pyomo 6.5.0 on a PC with a 6-core 3.50 GHz Intel(R) Xeon(R) E5-1650 processor and 64 GB of RAM. The runtimes for the above three cases are 1.22s, 11.80s and 15.53s, respectively.

B. Investment Decisions and Market Outcomes

The investment decisions and the associated carbon emissions and the business cases for three carbon cases are presented and compared in Table I. Figure 2 illustrates the dispatches of both existing and new-invested generators for three carbon cases. Figure 3 shows the hourly market clearing prices and business cases for three carbon cases.

TABLE I: Investment decisions, carbon emissions, and business cases for different carbon targets

Carbon cases	HC	LC	ZC
CCGT (MW)	300	100	0
OCGT (MW)	0	0	0
Nuclear (MW)	0	0	100
Wind (MW)	0	950	800
Carbon emissions (t)	421.90	43.80	0.00
Investment cost (mil.£)	4.32	35.41	36.09
Energy cost (mil.£)	22.37	2.32	4.14
Revenue (mil.£)	34.28	43.28	40.23
Profit (mil.£)	7.58	5.55	0.01

1) *Investment Decisions*: It can be observed that nuclear and WT technologies are prioritized to invest with the decline in carbon targets. Specifically, in contrast with entirely investing in the high-pollution CCGT technology for the HC case, the investment mix of the LC case involves lower CCGT capacity and substantial WT capacity at 950 MW. For the ZC case, nuclear and WT technologies account for 100% of the new-invested generation mix, benefiting from their carbon-free characteristics.

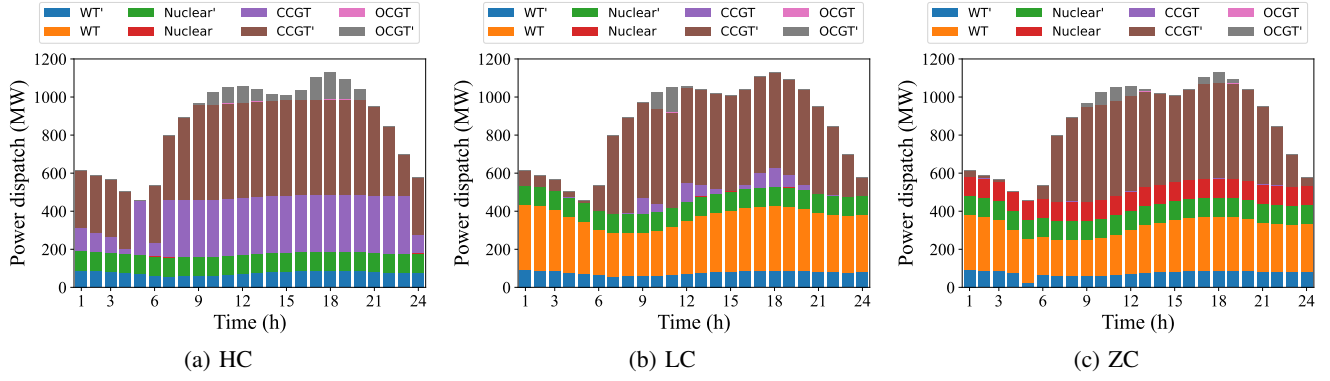


Fig. 2: Daily power dispatches of both existing (e.g., WT') and new (e.g., WT) technologies for three carbon cases.

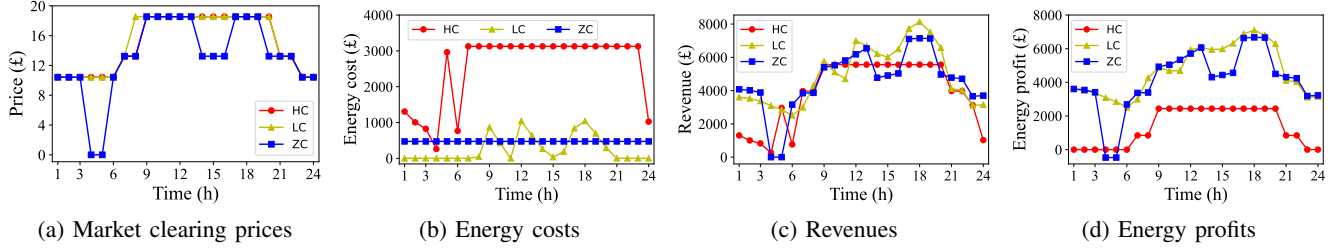


Fig. 3: Daily market clearing prices and business results for three carbon cases.

2) *Carbon Emissions*: In terms of the environmental effect, carbon emission is significantly reduced by 90% from the HC case (421.90 t) to the LC case (43.80 t) and finally reaches complete zero at the ZC case.

3) *Business Cases*: First of all, let us analyze the investment cost as presented in Table I. The investment costs, which are only related to investment decisions, dramatically increase with the reduction of carbon emissions. This trend is driven by two factors: i) compared with the flexible generation technology of CCGT, the investment costs of zero-carbon generation technologies of nuclear and wind generation are much higher; ii) the invested capacities of wind are significantly high in both LC and ZC cases.

Secondly, let us analyze the energy cost for different carbon cases. It should be mentioned that the energy cost is determined by the power dispatches and the corresponding marginal costs. For the HC case as depicted in Figure 2a, the energy supply is mainly supported by the flexible generation technologies of CCGTs (purple and brown) with high marginal costs. In this case, the energy costs for each time period are high, as shown in Figure 3b. On the other hand, more wind power dispatches (orange) are replacing the conventional CCGT technology (purple) in the LC case as shown in Figure 2b, therefore resulting in low energy cost and even zero energy cost for some off-peak periods, given by the zero marginal cost wind generation. Finally, once nuclear (red in Figure 2c) is invested in the ZC case, it runs all the time due to its full-operation characteristic, resulting in a flat energy cost, as shown in Figure 3b.

Thirdly, let us analyze the revenue for different carbon cases. It can be observed from Figure 3a that the market clearing prices are the same for HC and LC cases, which means the revenue is solely affected by the power dispatches. Obviously, the higher investment capacity in the LC case will generate more power dispatches, and the zero marginal

cost WT is further to be dispatched in high priority due to the merit-order principle. In this case, the revenue of the LC case (43.28 mil.£) is higher than that of the HC case (34.28 mil.£). For the ZC case, the high marginal cost technology of CCGT is replaced by nuclear and WT, resulting in a lower market clearing price profile, as depicted in Figure 3a. In this case, the revenue of the ZC case is relatively decreased by 3.05 mil.£ compared to that of the LC case.

Finally, it might be very interesting to analyze the profit trends for different carbon cases. In the generation planning problem, the profit is defined by the differences between the revenue and the sum of investment and energy costs. It can be observed from Table I that the profit is reduced with the restriction of the carbon target, this is because the investment costs of zero-carbon technologies (nuclear and WT) are very expensive, and are not capable to offset the increased revenues and the reduced energy costs.

IV. CONCLUSIONS

This paper establishes a bi-level optimization problem to investigate the impact of carbon targets on generation planning strategies, where the GenCo is formulated in the UL problem and the market clearing algorithm is formulated in the LL problem. To solve this problem, the MPEC approach and strong duality theorem are adopted. Case studies have demonstrated that the tight carbon target will force examined GenCo to invest in substantial nuclear and RES technologies, and subsequently reduce the energy prices so as to reduce its net profit. In other words, the economic benefits cannot be captured with the environment concerns [17]. To this end, the future work aims to develop a more advanced market mechanism that can effectively balance both economic and environmental benefits of generation planning problem towards a cost-effective and low-carbon transition.

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APPENDIX A

NOMENCLATURE

A. Indices and Sets

t	Index of hours
$i/k/q$	Index of flexible / must-run / renewable generation technologies
$i'/k'/q'$	Index of existing flexible / must-run / renewable generation units
V^{LL}	Set of variables of the LL problem

B. Parameters

ω	Weighting factor of the representative day
C_i^{EN}/C_k^{EN}	Marginal energy cost of flexible / must-run generation technology i/k (£/MWh)
$C_{i'}^{EN}/C_{k'}^{EN}$	Marginal energy cost of existing flexible / must-run generation unit i'/k' (£/MWh)
$C_i^{IN}/C_k^{IN}/C_q^{IN}$	Investment cost of flexible / must-run / renewable generation technology $i/k/q$ (£/MW/yr)
$X_{i,b}/X_{k,b}/X_{q,b}$	b MW-investment option of new generation units using flexible / must-run / renewable generation technology $i/k/q$ (MW)
$G_{i'}/G_{k'}/R_{q'}$	Capacity of existing flexible / must-run / renewable generation unit $i'/k'/q'$ (MW)
L_t	Baseline demand at hour t (MW)
$\eta_i^{CO_2}$	Carbon intensity of flexible generation technology i (ton/MWh)
$\eta_{i'}^{CO_2}$	Carbon intensity of existing flexible generation unit i' (ton/MWh)
E^{CO_2}	Systematic CO_2 emissions limitation for generation investment (ton)
$E^{CO_2'}$	Systematic CO_2 emissions limitation for existing generation units (ton)
$k_{q,t}$	Normalized output of renewable generation technology q at hour t
$k_{q',t}$	Normalized output of existing renewable generation unit q' at hour t

C. Continuous decision variables

$G_i/G_k/R_q$	Total capacity of new flexible / must-run / renewable generation units using technology $i/k/q$ (MW)
$g_{i,t}/g_{k,t}/r_{q,t}$	Power output of new generation units using flexible / must-run / renewable generation technology $i/k/q$ at hour t (MW)
$g_{i',t}/g_{k',t}/r_{q',t}$	Power output of existing flexible / must-run / renewable generation unit $i'/k'/q'$ at hour t (MW)
<i>D. Integer decision variables</i>	
$N_{i,b}/N_{k,b}/N_{q,b}$	Number of new generation units with capacity of b MW-investment option using flexible / must-run / renewable technology $i/k/q$