Electrical Power and Energy Systems 156 (2024) 109713

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Optimal self-unit commitment with shared asset ownership under realistic taxation in the current decarbonization framework

Pedro Otaola-Arca, Javier García-González *, Pedro Linares

Institute for Research in Technology, ICAI School of Engineering, Universidad Pontificia Comillas, Santa Cruz de Marcenado, 26, 28015, Madrid, Spain

ARTICLE INFO

Keywords:
Electricity market
Tax scheme
Shared ownership
Profit maximization
Self-unit commitment (self-UC)
Carbon Capture and Sequestration (CCS)

ABSTRACT

Energy, greenhouse gas emissions, or water taxes, are present in many power systems as available instruments to implement energy, environmental or climate policies. The goal of these taxes is to change producers' optimal behavior and hence achieve a cleaner operation. However, these changes in operation are not straightforward to simulate when producers are price makers, or when assets are owned jointly by different agents. State-of-the-art models are unable to consider differentiated income taxes per technology or geographical region, in the case of price makers. In this paper, we present a novel formulation that models the individual market income of each unit using the binary-expansion technique to address the case of a price-maker agent. Unlike existing state-of-the-art formulations, our approach successfully accounts for differentiated income taxes per technology or geographical region and accurate market revenues of shared generators. The proposed model enables evaluating the rational behavior of a generation company confronting a complex yet realistic decision problem, under different types of taxes related to decarbonization or resource conservation policies. The case study incorporates the impact of the installation of carbon sequestration and storage equipment in a fleet of gas-fired power plants, yielding satisfactory numerical results.

1. Introduction

The need to decarbonize the electricity sector, and to make it compatible with a more sustainable future, has resulted in the introduction of many policies that try to reduce greenhouse gas emissions or water use, something that is expected to become much more relevant in the future [1]. These policies are frequently designed as taxes, charged over emissions or over market revenues, and are already in place in many regions. Although market income taxes themselves cannot be directly categorized as environmental taxes, they can be utilized to achieve environmental goals by imposing higher charges on incomes obtained from pollutant generators. All these taxes in turn are expected to change the operation of generation plants, hopefully reducing their environmental impact. However, their impact will depend on how they are implemented: in some cases (e.g. carbon taxes) they change marginal costs, and in others (e.g. water charges, or paying for support schemes to encourage the deployment of specific technologies) they may be even fixed amounts, not related to the energy produced. Besides from environmental taxes, windfall taxes are also considered in some markets. When affecting variable costs, these taxes will in turn change the optimal operation depending on how generation companies (GenCos) are able to pass them through in their market bids [2]. In all cases, they will affect the efficiency and equity of these policies. Therefore, their correct representation is essential to understand how they will change market outcomes.

Unfortunately, despite the large number of works that have studied the optimal scheduling problem from a technical point of view (start-up and shut-down power trajectories, time-dependent start-up costs, non-convex input output costs, relationship between power output and available reserves, etc.), state-of-the-art models tend to oversimplify how these taxes affect the operation of the GenCos. The term self-unit commitment (self-UC) is the problem faced by one generation company that participates in the electricity market that needs to plan the optimal hourly scheduling and corresponding start-up and shutdown decisions of its own generation assets. This kind of model is needed in a liberalized electricity market where each company is responsible for planning its own generators' operation as a preliminary step to submitting their offers to the market. For that reason, it has been a fruitful research topic since the liberalization of the electric power industry took place. Given the diversity of possible market designs, it is necessary to accommodate specific market rules in the decision-making process. In addition, the impact of a GenCo's actions on the resulting market prices might be relevant. When such influence is

* Corresponding author.
E-mail addresses: pedrotaolarca@alu.comillas.edu (P. Otaola-Arca), javiergg@iit.comillas.edu (J. García-González), pedro.linares@iit.comillas.edu (P. Linares).

https://doi.org/10.1016/j.ijepes.2023.109713
Received 27 March 2023; Received in revised form 4 August 2023; Accepted 7 December 2023

negligible, the GenCo can be considered a price-taker, and market prices can be treated as exogenous variables that can be predicted by different techniques. In the opposite case, the GenCo can be considered as a price-maker, and the dependence of market prices on the actions must be embedded in the decision-making process. In both cases, the optimal scheduling problem can be formulated as the maximization of the profit defined as the difference between market incomes and operational costs. The impact of the uncertainty is also important. For the case of a price-taker, the GenCo can find the optimal scheduling of its units assuming as input data possible spot-prices scenarios [3]. However, for a price-maker, it is necessary to model its competitors' uncertain behavior, which can be achieved by using residual demand curve scenarios.

The residual demand curve expresses the market price in a time period as a function of the total quantity produced by the price-maker agent. As both the price and the quantity are decision variables, their product leads to a non-linearity that complicates the resolution of the resulting optimization problem. The idea of overcoming this difficulty by building the corresponding income (or revenue) functions was first published in [4], where the authors extended and improved a previous work limited to quadratic income functions. Under this approach, the income functions could be modeled as piece-wise linear functions using binary variables and embedded into mixed-integer linear programming (MILP). In [5] the authors apply the same approach taking into account the detailed step-wise residual demand curves that can be built assuming perfect knowledge about the offers and bids submitted by the rest of market participants, which is extended to not only the energy but several reserve markets in [6]. In [7], the number of binary variables required to model the income functions is reduced by identifying the intervals where the approximated piece-wise linear income functions are concave. This approach can be advantageous to reduce the computational burden in the presence of uncertainty [8]. In [9] the authors use this approach to perform a self-UC for a whole week.

All those previous works require introducing as input data the residual demand curves. This entails forecasting the offers and bids of a GenCo's competitors [10,11], and the increasing presence of non-dispatchable renewable energy sources can make this forecast even harder as the shape of the offer curves changes dynamically [12]. In addition, when complex bids are allowed, the construction of hourly residual demand curves requires additional processing as suggested in [13].

In addition to methods that use residual demand scenarios, an alternative approach is to estimate competing firms' bids and explicitly represent the market-clearing algorithm, resulting in a bilevel problem. In [14], the resulting mathematical programming with equilibrium constraints (MPEC) is solved by formulating its equivalent MILP and applying the binary expansion method. The same approach is used in [15], but in this case, instead of optimizing the decision of one single GenCo, the whole Nash Equilibrium is formulated to estimate the short-term decisions of all the involved market participants. A similar approach is used in one of the models of [16,17] to evaluate flexible resources in two-settlement electricity markets (day-ahead and real-time).

All those previous works express the incomes of the GenCo through an aggregated portfolio approach. When a tax depends on a particular generator's market income, such a portfolio approach cannot consider separate charges for each power plant. In addition, when the generating asset is owned jointly by several agents, the portfolio approach can neither represent the income of such generator appropriately as the market-clearing for each possible market price is uncertain, as it will be explained in 3.3.1.

In this paper, we propose a novel approach that addresses these limitations and hence allows for correctly representing how environmental or income taxes may change the operation of GenCos and their environmental impact. The main contributions can be summarized as follows: (1) to present systematically the different taxes that affect the optimal operation of the GenCos in current markets, (2) to overcome the drawbacks of the state-of-the-art approaches when modeling partially owned units, and taxes applied to market incomes of a price-maker GenCo, (3) to present the detailed mathematical formulation —based on the binary expansion technique—where the individual market incomes of each generation unit are modeled, (4) the adaptation and application of the proposed model to assess the impact of installing Carbon Sequestration and Storage (CCS) equipment taking into account the strategic behavior of the GenCo, and (5) to present the stochastic self-UC formulation that incorporates the proposed modeling that has been applied successfully to realistic example cases as shown in the results section.

The remainder of the paper is organized as follows. Section 2 describes energy taxation affecting the electricity market. Considerations regarding price-maker modeling approaches are discussed in 3. The mathematical formulation is shown in 4. Finally, the study case is presented in 5, and the main conclusions are summarized in 6.

2. Energy taxation affecting the electricity market equilibrium

There are many ways in which taxes can be used in the power sector (see e.g. [1] for an extensive review).

- Some taxes are Pigouvian, trying to internalize the different externalities produced by the generation of electricity. These Pigouvian taxes may be imposed over the emissions released, the land used, or the water polluted, since these are the drivers of the externalities. In some cases, because of the difficulty in measuring emissions or pollution, the amount of electricity produced, or the amount of fuel used can be used as proxies for the externalities.
- Other taxes, such as those imposed on the fuels, try to capture the scarcity rents created by exhaustible resources. However, their use is not too common in the power sector, since they are typically intermediate inputs. Water taxes are however an exception here: they are commonly used to capture in part the scarcity rent created by the typically free concession of water rights. Another recent example is the windfall tax created to reduce the windfall profit of some generators because of increasing CO_2 prices.
- The third category of taxes includes charges needed to finance infrastructures or policy measures. This would be the case of the renewable charges or levies imposed generally on end consumers (on top of the total electricity cost), but also on retailers or sometimes generators (as in the 7% tax used in the Spanish power sector or charges to finance energy poverty measures).

The impact of these taxes will be different based on whether they are variable or fixed; or on the tax base used: electricity produced (or sold), fuel (or water) used, carbon emissions, revenues, profits, or even more complicated ones, such as when applying a windfall tax to compensate CO_2 price changes. This will determine not only how costs are passed through to consumers, but also the optimal operation strategy of the system. For example, if CO_2 costs pass-through is not allowed (as in Chile) then there will be no incentive to operate low-carbon technologies. Therefore, a correct representation of these different taxes is essential to understand their impact on the power system's operation. From a mathematical point of view, taxes can be considered in various ways depending on their nature. Although taxation policies can be very diverse, this paper identifies four taxes present in current systems whose consideration in an optimization model requires some discussion: taxes applied to the electricity generation (energy), taxes applied to the amount of fossil fuel consumed, taxes applied to carbon emissions, and finally, taxes applied to market revenues. As discussed later, the last one can be very challenging when formulating the profit maximization problem for a price-maker participant.

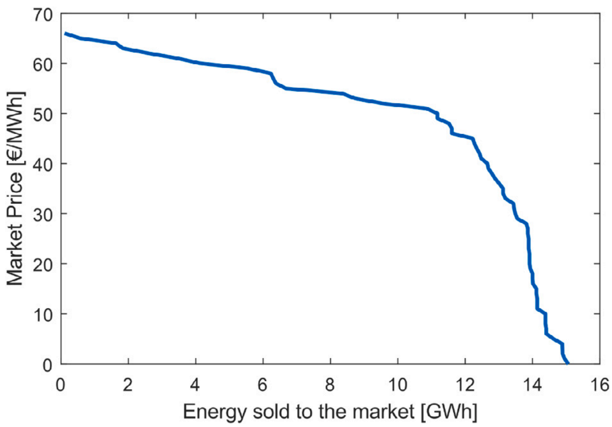

Fig. 1. Residual demand curve (Iberian system H14 15/7/2013).

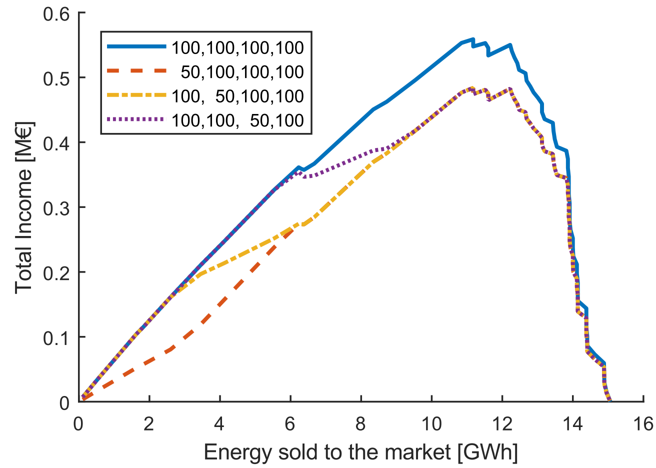

Fig. 2. The solid line represents the income function for full ownership of all the involved plants. Dashed lines show the income functions that would result when one unit is partially owned (50%) for different clearing orders (first, second and third).

3. Price maker modeling approaches

3.1. General definitions

In the day-ahead market, participants submit bids as a set of quantity-price pairs. The Market Operator builds the aggregated supply curve $S(q)$ and demand curve $D(q)$, and finds the market clearing price p by solving $S(q) = D(q) = p$. Given a GenCo, assuming that $Sb(q)$ is the aggregated supply curve of all its competitors, the residual demand curve $R(q)$ can be obtained as $R^{-1}(p) = D^{-1}(p) - Sb^{-1}(p)$. Therefore, $R(q)$ expresses the market price p as a function of the total power produced and sold by the GenCo, i.e. $p = R(q)$ [4,13]. An example of a residual demand curve for an hour is shown in Fig. 1.

In order to maximize profits, it is necessary to include market income in the objective function. For a price-maker agent, the resulting optimization problem would be non-linear as the income term involves the product of two variables (quantity produced, and system marginal price) extended to all the time periods considered in the optimization.

3.2. The state-of-the-art approach: portfolio income functions

The approach proposed in the literature to deal with such non-linearity consists in calculating this product ex-ante as an income curve and including it as a parameter in the model. The curve $I(q) = q \cdot p = q \cdot R(q)$ represents the total income of a GenCo in a given hour as a function of its energy sold on the market in that hour. For each amount of energy, the total income is the energy times the corresponding price in the residual demand curve for that amount of energy. The resulting income curve calculated with the residual demand curve of Fig. 1 is displayed in solid blue in Fig. 2. This curve can be approximated by a piece-wise linear function applying statistical and heuristic methods that balance the accuracy and complexity of the obtained approximation. In particular, the method described in [18] has been used in this paper.

Once the hourly income curves are approximated by piece-wise linear functions, the resulting problem can be solved as a MILP optimization. According to the technical literature, the preference for formulating the problem as MILP rather than a non-linear optimization stems from the advantages offered by MILP solvers, such as computational efficiency, ability to find global optima, handling of discrete decisions, and scalability for large-scale problems. In principle, a binary variable is needed for each linear segment, and consequently, it is necessary to include additional constraints to ensure that those segments are filled in order. However, when maximizing the profit, the optimizer will fill the segments starting with those with the steepest slope. Therefore, segments can be grouped into concave intervals and ensure that such intervals are filled in order by assigning binary variables to them. This results in a more efficient formulation because the number of binary variables required is reduced as there are fewer concave intervals than segments. Fig. 3 shows an example of a discretized income curve with its segments s and concave intervals c, for a particular hour t and scenario w. For the first hour and scenario ($t = 1$ and $w = 1$) the relation between s and c according to set $\Omega^{cs}_{w,t}$ would be $s = \{1, 2\} \in \Omega^{cs}_{w,t}$ for $c = 1$, and $s = \{3, 4, 5, 6\} \in \Omega^{cs}_{w,t}$ for $c = 2$. Regarding possible segments s in that hour and scenario according to set $\Omega^{s}_{w,t}$, it would be $s = \{1, 2, 3, 4, 5, 6\} \in \Omega^{s}_{w,t}$.

3.3. Drawbacks of the formulation based on income functions

3.3.1. Shared ownership of generation plants

When a company owns 100% of the assets it manages, the income curve can be computed as explained in the previous section. However, when the assets are not 100% owned by the company, the income curves have to be corrected accordingly. For example, if a company owns 80% of a 1000 MW power plant, the income that corresponds to 1000 MWh is equal to 800 MWh times the electricity price. In this sense, if the order in which the different groups are going to be cleared could be known beforehand, it could be possible to represent the correct income curve. However, if such a sequence cannot be predefined, it is impossible to accurately represent the GenCo income. For instance, several income curves for different ownership percentages and clearing sequences are shown in Fig. 2. Notice that in the presence of shared power plants, it is impossible to build a unique income curve for each hour, which is a mandatory condition to use the portfolio income functions, and therefore, the existence of shared generators invalidates the state-of-the-art approach.

3.3.2. Income tax

Generation, fuel consumption, and emission taxes can be formulated linearly by multiplying the corresponding variable (generation, consumption, or emissions) by its per-unit tax, which is an input-data parameter. However, computing the tax applied to the market incomes is not so straightforward as it depends on the product of two variables: the market price and the quantity sold in the market. One possible solution would be to modify the aggregated income function of the GenCo by multiplying it by a scaling-down factor so that the resulting curve reflects the net revenue after such tax. However, this approach would be accurate only in case all the power plants belonging to the GenCo were affected by the same per-unit tax, or in case the mapping between the total power sold in each time period and the individual

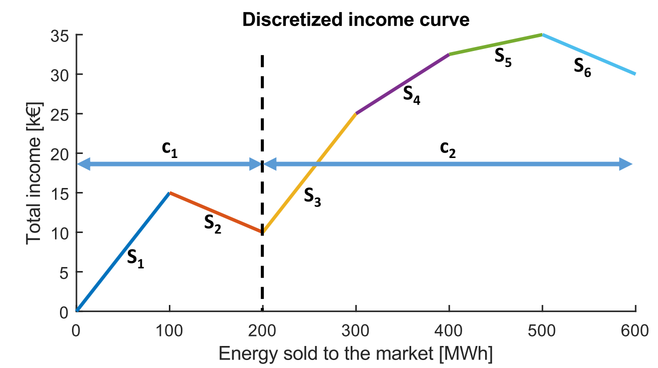

Fig. 3. Illustrative income curve discretization example with segments s and concave intervals c.

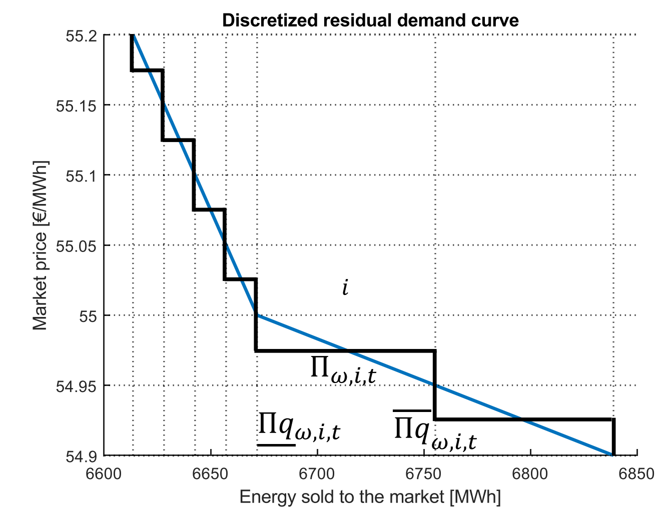

Fig. 4. Residual demand curve discretization example with a 0.05€ step for a segment i. $\Pi_{w,i,t}$: segment price; $\underline{\Pi q}_{w,i,t}$: segment minimum power; $\overline{\Pi q}_{w,i,t}$: segment maximum power.

production of each generator was known beforehand, which is not realistic. To illustrate this idea, let us see what would happen with an example of three groups in different cases:

• Case A: all three units have an income tax of 4%. In this case, the income curve is multiplied by 0.96, the resulting income already accounts for the 4% tax, and the representation is 100% accurate.

• Case B: two of the units have an income tax of 4%, and another has a 6% tax. In this case, if the same approach is followed and the income curve is multiplied by 0.96, the results would underestimate the tax impact in 6 − 4 = 2% of the income of the third generator. Approximations could be additionally applied to minimize the error's impact; for instance, one possibility is explained in Section 4.2.

In the Iberian market, for example, the tax applied to hydro generation is different than the one applied to gas generation; and both countries, Spain and Portugal, participate in the same market although they have different tax schemes.

4. Mathematical formulation

The presented self-UC model can help the GenCo to find the optimal UC and hourly scheduling of its own generators in a market environment. The formulation of all the typical UC constraints such as ramp limits, minimum up and down times, start-up and shutdown trajectories, start-up types, etc. have been omitted here for the sake of simplicity and have been included in the Appendix.

Section 4.1 presents the proposed formulation using generators' individual income whereas 4.2 presents the common approach found in the literature based on portfolio aggregated income curves.

4.1. Proposed formulation

For this formulation, the residual demand curve is discretized with fixed steps in the price axis. In Fig. 4 a discretization example is displayed.

The objective function (1) is to maximize the GenCo's expected profit: the sum extended to all its generators of the difference between incomes $rG_{w,g,t}$ and costs $csG_{w,g,t}$ multiplied by the scenario probability $Prob_w$:

$$\max \left(\sum_{\substack{w\in W\\ g\in G t\in T}} \left[Prob_w \left(rG_{w,g,t} - csG_{w,g,t} \right) \right] \right) \tag{1}$$

The generator's individual income (2) is the price of each residual demand curve segment $\Pi_{w,i,t}$ times the power output in each segment $k_{w,i,g,t}$. Notice that as this variable is defined for each generation unit, the potential reduction due to taxes or shared ownership can be easily taken into account multiplying by the ownership percentage Own_g.

$$rG_{w,g,t} = Own_g \sum_{i\in I} \left[\Pi_{w,i,t} \cdot k_{w,i,g,t} \right] \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{2}$$

Eq. (3) ensures that only one segment of each residual demand curve is active for each time period by making the sum of all the activation variables $a_{w,i,t}$ for each segment i equal to one.

$$\sum_{i\in I} \left[a_{w,i,t} \right] = 1 \quad \forall w \in W, \forall t \in T \tag{3}$$

Eqs. (4) and (5) locate the active segment i of the residual demand curve as a function of the total generation, being $pt_{w,g,t}$ the power output of each generation unit. The binary variable of activation of the residual demand segment $a_{w,i,t}$ is 1 for the segment which has a minimum (maximum) power $\underline{\Pi q}_{w,i,t}$ ($\overline{\Pi q}_{w,i,t}$) lower (higher) than the total generation.

$$\sum_{g\in G} \left[pt_{w,g,t} \right] \geq \sum_{i\in I} \left[a_{w,i,t} \cdot \underline{\Pi q}_{w,i,t} \right] \quad \forall w \in W, \forall t \in T \tag{4}$$

$$\sum_{g\in G} \left[pt_{w,g,t} \right] \leq \sum_{i\in I} \left[a_{w,i,t} \cdot \overline{\Pi q}_{w,i,t} \right] \quad \forall w \in W, \forall t \in T \tag{5}$$

The generator total power output (6) is equal to its power in all the residual demand curve segments:

$$pt_{w,g,t} = \sum_{i\in I} \left[k_{w,i,g,t} \right] \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{6}$$

The relation between the power output of the generator and the active residual demand curve segments is established using a big-M type constraint (7) that uses the maximum power output of each unit $\overline{P}_{g,t}$ as the tighter bound.

$$k_{w,i,g,t} \leq a_{w,i,t} \cdot \overline{P}_{g,t} \quad \forall w \in W, \forall i \in I, \forall g \in G, \forall t \in T \tag{7}$$

The operation and maintenance cost of each generator $csOM_{g,t}$ is computed in (8) considering the hours of use and the number of start-up maneuvers. The UC variables for the start-up decisions $y_{g,t}$ and commitment status $v_{g,t}$ are multiplied by the cost associated to the start-up maneuvers $OMsu_g$ and the cost per hour of operation OMh_g.

$$csOM_{g,t} = Own_g \left(OMsu_g \cdot y_{g,t} + OMh_g \cdot v_{g,t} \right) \quad \forall g \in G, \forall t \in T \tag{8}$$

The fuel consumption of each generator $cnG_{w,g,t}$ is computed in (9), and its associated cost $csCN_{w,g,t}$ is calculated in (10). In (9), the parameters $CNsu_{g,su}$, $CNsd_g$, $CNmn_g$ and $CNvr_g$ represent the fuel consumption associated to each start-up (type dependant) and shut down maneuvers, minimum consumption during operation, and power dependant consumption, respectively. The variables $\delta_{g,t,su}$, $z_{g,t}$, and $p_{w,g,t}$ correspond to the start-up (type dependant) and shut-down decisions and the power output above the minimum stable load. The fuel price PCN_g is used for the cost calculation.

$$cnG_{w,g,t} = \sum_{su} \left[CNsu_{g,su} \cdot \delta_{g,t,su}\right] + CNsd_g \cdot z_{g,t} + CNmn_g \cdot v_{g,t} + CNvr_g \cdot p_{w,g,t} \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{9}$$

$$csCN_{w,g,t} = Own_g \cdot cnG_{w,g,t} \cdot PCN_g \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{10}$$

The cost of each generator (11) is calculated as the fuel consumption cost plus the O&M cost $csOM_{g,t}$ plus all the taxes applied to the generation unit $txG_{w,g,t}$ (aggregated in (12)). Notice that all those terms have already considered the ownership percentage of the units.

$$csG_{w,g,t} = csCN_{w,g,t} + csOM_{g,t} + txG_{w,g,t} \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{11}$$

$$txG_{w,g,t} = txCN_{w,g,t} + tx\text{CO2}_{w,g,t} + txE_{w,g,t} + txI_{w,g,t} \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{12}$$

The following equations compute the costs for the different taxes that may exist. The cost of the tax applied to fuel consumption $txCN_{w,g,t}$ is calculated with the consumption variable and the tax rate $TxCN_g$ (13). The cost of an emission tax $tx\text{CO2}_{w,g,t}$ is computed with the consumption variable, a ratio regarding emission per fuel consumption $\text{CO2}r_g$, and the emission tax rate $Tx\text{CO2}$ (14). For the generation tax cost $txE_{w,g,t}$, the total generation of the unit and the tax rate TxE_g are taken into account (15). Finally, the income tax cost $txI_{w,g,t}$ uses the individual revenue variable and the income tax TxI_g (16).

$$txCN_{w,g,t} = Own_g \cdot cnG_{w,g,t} \cdot TxCN_g \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{13}$$

$$tx\text{CO2}_{w,g,t} = Own_g \cdot cnG_{w,g,t} \cdot \text{CO2}r_g \cdot Tx\text{CO2} \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{14}$$

$$txE_{w,g,t} = Own_g \cdot pt_{w,g,t} \cdot TxE_g \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{15}$$

$$txI_{w,g,t} = rG_{w,g,t} \cdot TxI_g \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{16}$$

4.2. Formulation using portfolio income curves

The objective function (17) is to maximize the expected profits by subtracting the cost from the revenue calculated with the income curve $rT_{w,t}$.

$$\max \left(\sum_{\substack{w \in W \\ t \in T}} \left[Prob_w \left(rT_{w,t} - \sum_{g \in G} \left[csG_{w,g,t} \right] \right) \right] \right) \tag{17}$$

The income in each period (18) is computed as the income in each segment of the income curve. The power assigned to each segment is represented by the variable $qI_{w,s,t}$ and the slope of the segment is the parameter $Islp_{w,s,t}$.

$$rT_{w,t} = \sum_{s \in \Omega^s_{w,t}} \left[Islp_{w,s,t} \cdot qI_{w,s,t} \right] \quad \forall w \in W, \forall t \in T \tag{18}$$

The total power generation of the units is equal to the power for the income curve (19).

$$\sum_{g \in G} \left[pt_{w,g,t} \right] = \sum_{s \in \Omega^s_{w,t}} \left[qI_{w,s,t} \right] \quad \forall w \in W, \forall t \in T \tag{19}$$

Eqs. (20) and (21) ensure that the binary variable of activation of the concave intervals $qbinI_{w,c,t}$ is 0 for the intervals that have not filled all their power and 1 for those that have. These equations also imply that intervals are activated in order, and it is assumed that $qbinI_{c-1,t} = 1$ for $c = 1$. The parameters $\overline{Iq}_{w,s,t}$ and $\underline{Iq}_{w,s,t}$ are the maximum and minimum power of each segment of the income curves.

$$qI_{w,s,t} \geq \left(\overline{Iq}_{w,s,t} - \underline{Iq}_{w,s,t} \right) qbinI_{w,c,t} \quad \forall w \in W, \forall t \in T, \forall (c,s) \in \Omega^{cs}_{w,t} \tag{20}$$

$$qI_{w,s,t} \leq \left(\overline{Iq}_{w,s,t} - \underline{Iq}_{w,s,t} \right) qbinI_{w,c-1,t} \quad \forall w \in W, \forall t \in T, \forall (c,s) \in \Omega^{cs}_{w,t} \tag{21}$$

Eq. (22) establishes the order in which the concave intervals are activated. This equation is theoretically redundant with (20) and (21), but according to the numerical test carried out during the preparation of the case study, its inclusion can be helpful to reduce the computational burden.

$$qbinI_{w,c,t} \leq qbinI_{w,c-1,t} \quad \forall w \in W, \forall t \in T, \forall c \in C - \{1\} \tag{22}$$

In addition, it would be necessary to compute the generation costs and see how taxes can be taken into account. The standard equation would be (23a), where the total cost accounts for the fuel consumption cost computed using (9) and (10), plus the O&M cost (8):

$$csG_{w,g,t} = csCN_{w,g,t} + csOM_{g,t} \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{23a}$$

Regarding taxes, to accurately represent fuel consumption, carbon emissions, and electricity generation taxes, they should be calculated with the previously presented Eqs. (13), (14) and (15). The resulting cost equation considering these taxes would be (23b):

$$csG_{w,g,t} = csCN_{w,g,t} + csOM_{g,t} + txCN_{w,g,t} + tx\text{CO2}_{w,g,t} + txE_{w,g,t} \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{23b}$$

Finally, profit taxation should be tackled. If the tax rate is exactly the same for all generating units, the precise way to express it would be to modify Eq. (18) by multiplying the revenue expression by one minus such common tax rate TxC. However, if the units have a tax other than this common rate, the only way to represent it would be in an approximate manner, which is the main drawback of the state-of-the-art approach. This approximation can be made, for example, by artificially increasing the cost of the unit by a factor. That factor could be calculated as the inverse of the difference between the minimum common tax and the particular one of the generator that exceeds that common value. With this approximation, the resulting cost equation would be (23c).

$$csG_{w,g,t} = \frac{csCN_{w,g,t} + csOM_{g,t} + txCN_{w,g,t} + tx\text{CO2}_{w,g,t} + txE_{w,g,t}}{1 - \left(TxI_g - TxC\right)} \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{23c}$$

4.3. Formulation of carbon capture and sequestration

This paper considers a fleet of combined cycle gas turbine (CCGT) power plants. In order to illustrate how the proposed model can be used to mimic the optimal behavior of a GenCo and to assess the resulting CO_2 emissions under different taxation and price settings, we consider that the CCGTs' might have installed a post-combustion Carbon Capture and Sequestration (CCS) equipment [19]. CCS refers to the process of capturing CO_2 and posterior storage in geological formations. While there are still some technical, economic, and environmental challenges associated with CCS, it is considered to be a key technology for achieving deep decarbonization and meeting global climate goals.

The energy penalty (EP) of CCS refers to the additional energy required to capture, transport, and store the CO_2 emissions generated by the power plant. As a result, the net power output of the plant is reduced, and the cost of electricity generation increases. The energy penalty of CCS can be expressed as a percentage of the gross power output of the plant. For example, if a power plant has a gross power output of 100 MW and the energy penalty of CCS is 10%, then the net power output of the plant would be reduced by 10 MW. As in all the previous mathematical expressions the output power $pt_{w,g,t}$ was net power, in order to compute the corresponding gross power, in-house power consumption apart from the CCS will be considered as 4% of the gross power.

According to [20] the energy penalty of CCS in natural gas-fired power plants is typically between 8% and 12% of the gross power output. Other references such as [21] consider that the energy penalty can reach 14%. In [22] it is suggested to use storage for the CO_2 amine-rich solution in order to regenerate it in the time periods where the electricity is less expensive. In this paper, such inter-temporal management of the CCS electricity consumption will not be considered, and a constant energy penalty factor equal to 12% will be assumed for a capture rate of 90% of CO_2 emissions, [23]. Therefore, for a given scenario w, generation unit g and hour t, the energy penalty can be computed as follows:

$$\frac{pt_{w,g,t}}{0.96} \cdot 0.12 = pt_{w,g,t} \cdot 0.125 \tag{24}$$

Without CCS, for 100 MW of gross power, there will be 96 MW of net power. In the case of having CCS equipment, apart from the 4 MW of in-house power consumption, there will be an additional 12.5 MW of energy penalty. Thus, the net power to be injected into the grid will be 100-4-12.5 = 83.5 MW. The ratio between the net power without-CCS and with-CCS will be 83.5/96 ≈ 0.87. Therefore, in terms of modeling, the equations that represent the internal functioning of the power plant and all the incurred cost are the same as in the case without CCS with the only difference that the effective output power to be sold to the market would be reduced by an energy penalty factor equal to $\rho^{ep} = 0.87$.

Let G^{ccs} be the set of CCGT's units with CCS. The changes that need to be introduced in the proposed strategic self-UC mathematical formulation presented previously consist in substituting the term $pt_{w,g,t}$ by $\rho_g^{ep} \cdot pt_{w,g,t} \forall g \in G^{ccs}$ whenever necessary (notice that for the sake of generality, a different value of the energy penalty factor could be set for each generator). Therefore, Eqs. (4), (5), (6), (15) must substituted by (25), (26), (27), (28), (29), (30)

$$\sum_{g \notin G^{ccs}} \left[pt_{w,g,t}\right] + \sum_{g \in G^{ccs}} \left[\rho_g^{ep} \cdot pt_{w,g,t}\right] \geq \sum_{i \in I} \left[a_{w,i,t} \cdot \underline{\Pi q}_{w,i,t}\right] \quad \forall w \in W, t \in T \tag{25}$$

$$\sum_{g \notin G^{ccs}} \left[pt_{w,g,t}\right] + \sum_{g \in G^{ccs}} \left[\rho_g^{ep} \cdot pt_{w,g,t}\right] \leq \sum_{i \in I} \left[a_{w,i,t} \cdot \overline{\Pi q}_{w,i,t}\right] \quad \forall w \in W, \forall t \in T \tag{26}$$

$$pt_{w,g,t} = \sum_{i \in I} \left[k_{w,i,g,t}\right] \quad \forall w \in W, g \notin G^{ccs}, \forall t \in T \tag{27}$$

$$\rho_g^{ep} \cdot pt_{w,g,t} = \sum_{i \in I} \left[k_{w,i,g,t}\right] \quad \forall w \in W, \forall g \in G^{ccs}, \forall t \in T \tag{28}$$

$$txE_{w,g,t} = Own_g \cdot pt_{w,g,t} \cdot TxE_g \quad \forall w \in W, \forall g \notin G^{ccs}, \forall t \in T \tag{29}$$

$$txE_{w,g,t} = Own_g \cdot pt_{w,g,t} \cdot TxE_g \cdot \rho_g^{ep} \quad \forall w \in W, \forall g \in G^{ccs}, \forall t \in T \tag{30}$$

In addition, as the net maximum output power is also affected, (7) must be substituted by (31) and (32):

$$k_{w,i,g,t} \leq a_{w,i,t} \cdot \overline{P}_{g,t} \quad \forall w \in W, i \in I, g \notin G^{ccs}, t \in T \tag{31}$$

$$k_{w,i,g,t} \leq a_{w,i,t} \cdot \rho_g^{ep} \cdot \overline{P}_{g,t} \quad \forall w \in W, \forall i \in I, \forall g \in G^{ccs}, \forall t \in T \tag{32}$$

Table 1
Generation units data.

Parameters	Units	G1	G2	G3	G4	G5
Own_g	[p.u.]	1.00	0.90	1.00	1.00	1.00
$CNmn_g$	[MWh_t/h]	304	435	450	450	445
$CNvr_g$	[MWh_t/MWh]	1.59	1.30	1.60	1.60	1.50
$CNsu_{g,su=1}$	[MWh_t]	537	549	572	572	558
$CNsu_{g,su=2}$	[MWh_t]	726	729	675	675	747
$CNsu_{g,su=3}$	[MWh_t]	1026	983	1076	1076	1008
$CNsd_g$	[MWh_t]	67.83	65.85	65.30	65.30	63.50
$CO2r_g$	[ton/MWh_t]	0.19	0.19	0.19	0.19	0.19
$\overline{P}_g$	[MW]	385	400	390	390	400
$\underline{P}_g$	[MW]	128	200	185	185	180
$TmnS_{g,su=1}$	[h]	2	3	3	3	3
$TmnS_{g,su=2}$	[h]	12	12	12	12	12
$TmnS_{g,su=3}$	[h]	24	24	24	24	24
IS_g	0,1	1	1	0	0	1
IP_g	[MW]	100	140	0	0	140
TUo_g	[h]	6	6	0	0	6
TDo_g	[h]	0	0	12	12	0
$TmnOff_g$	[h]	2	3	3	3	3
$TmnOn_g$	[h]	2	2	2	2	2
RU_g	[MW/h]	55	74	70	70	70
RD_g	[MW/h]	55	74	70	70	70
TU_g	[h]	1	2	2	2	2
TD_g	[h]	1	1	1	1	1
$PU_{g,tu=1}$	[MW]	128.0	131.4	127.0	127.0	127.0
$PU_{g,tu=2}$	[MW]	–	200.0	185.0	185.0	180.0
$PD_{g,td=1}$	[MW]	0.0	0.0	0.0	0.0	0.0
TxE_g	[€/MWh]	1.00	1.00	1.00	3.00	1.00
TxI_g	[p.u.]	0.05	0.05	0.04	0.01	0.05
$TxCN_g$	[€/MWh_t]	2.5	2.5	2.5	2.5	2.5
PCN_g	[€/MWh_t]	20	20	20	20	20

Finally, to account for the 90% reduction of emissions thanks to the CCS equipment, Eq. (14) must be formulated only for units without CCS and complemented by (33):

$$txCO2_{w,g,t} = Own_g \cdot cnG_{w,g,t} \cdot CO2r_g \cdot (1 - 0.9) \cdot TxCO2 \quad \forall w \in W, g \in G^{ccs}, t \in T \tag{33}$$

5. Case study

The case study consists of the optimization of 5 CCGT units for the 24 h of the day-ahead power market. The default characteristics of the units are shown in Table 1, and CO_2 tax is $TxCO2$ = 21 €/ton. The residual demand curves for the Iberian market have been obtained with the model presented in [13] and are displayed in Fig. 5 (real data taken from the Iberian Electricity Market for the day 15/07/2013). All the date are online available in [24]. In order to highlight the capability of the proposed model to model the expected behavior of a strategic GenCo, the following analyses have been carried out:

- Validation of the proposed model with respect to the state-of-the-art approach in the absence of market particularities identified in this paper.
- Example to illustrate how the proposed model performs better than the state-of-the-art approach when facing different income taxes and shared ownership.
- Analysis of the model performance for different discretization steps of the residual demand curves.
- Example to illustrate how the model is able to capture that a slight change in the income tax between two identical units, leads to different results.
- Impact of CCS for different CO_2 taxes.
- Example of the stochastic model.

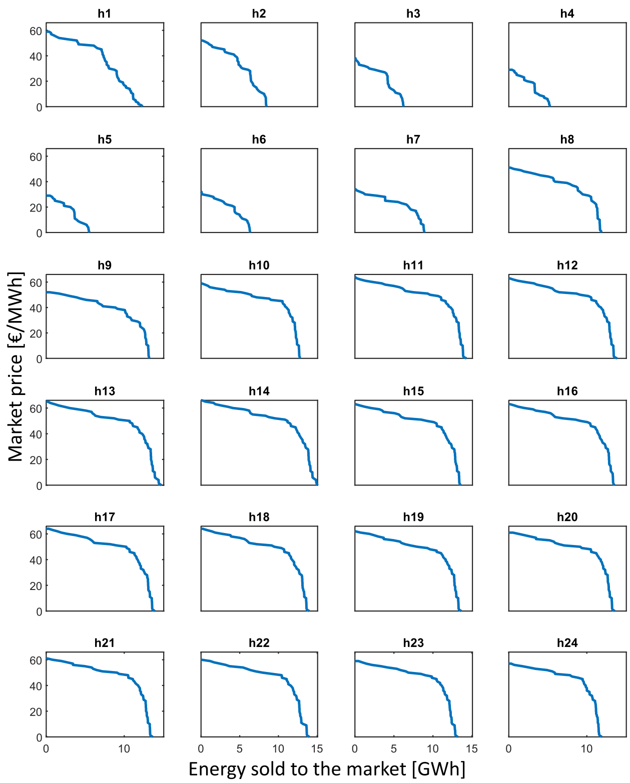

Fig. 5. Residual demand curves for the 24 h of the day.

Table 2
Model comparison with $Own_g = 1$ p.u., $TxE_g = 0.05$ p.u., and maximum level of detail (180 segments and 0.01 €/MWh). Ex-post terms are calculated with the non-discretized original curves.

Model	Individual inc.	Portfolio inc.
Discretization	0.01 [€/MWh]	180 [seg]
Continuous var. n°	126 230	5089
Binary var. n°	25 793	5040
Resolution time [s]	450.7	7.4
Income optimized [k€]	1421.27	1420.57
Taxes optimized [k€]	280.61	280.57
Cost optimized [k€]	1046.66	1046.67
Profits optimized [k€]	94.00	93.32
Income ex-post [k€]	1421.25	1421.28
Taxes ex-post [k€]	280.60	280.61
Cost ex-post [k€]	1046.66	1046.67
Profits ex-post [k€]	93.99	93.99
OPTCR [%]	0.00	0.00
Energy sold [GWh]	23.93	23.94

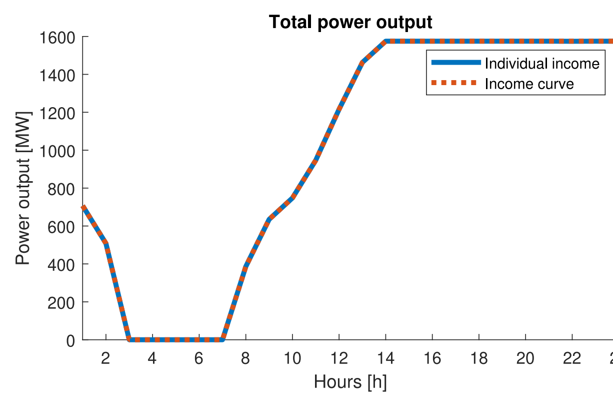

Fig. 6. Total generation for both models with $Own_g = 1$ p.u., $TxE_g = 0.05$ p.u., and maximum level of detail (180 seg and 0.01 €).

5.1. *Portfolio income vs. individual income with 100% ownership and equal taxes for all generators*

In order to assess the performance of the proposed model, this section presents a comparison between the state-of-the-art approach (portfolio income curve) and the proposed model (individual income per group) when facing a situation where the portfolio income curve is perfectly accurate, i.e. when the ownership of all the generation units is 100%, and when there are no differentiated taxes. In particular, a common value of 5% income tax has been assumed. The portfolio income curves have been modeled in a very detailed manner using 180 segments, and the residual demand curves have been discretized also in a very detailed way with a fixed step of 0.01 €/MWh. The results of this comparison are presented in Table 2 and the resulting generation schedule is displayed in Fig. 6. Magnitudes *"optimized"* are the values obtained by the solver at the optimization phase, whereas magnitudes *"ex-post"* are the accurate values that would result when using the actual residual demand curves without precision loss due to discretization.

It is important to highlight that the results of both models are practically the same, and this validates the proposed formulation confirming that both approaches are entirely equivalent in the absence of the particular issues (different taxes and shared ownership) raised in this paper. In that case, the state-of-the-art approach should be preferred as the number of variables and the computational time is smaller.

5.2. *Portfolio income curve vs. individual income with shared ownership and differentiated taxes*

This section also presents a comparison of both models, but in this case considering the default input data presented in Table 1 where generator G2 is owned partially ($Own_{G2} = 90\%$) and having different income taxes for generators G3 and G4: $TxI_{G3} = 4\%$ and $TxI_{G4} = 1\%$.

Table 3 presents the main results of this comparison, and the resulting generation schedule is displayed in Fig. 7. In this case, differences can be observed in the resulting schedule, and therefore in the profits obtained by each one of the models. From the analysis of Table 3 it can be observed that the proposed model with an individual income formulation for each generator obtains 0.52% better results ($100 \cdot (92.20-91.72)/91.72$). In addition, it should be noticed that the accuracy between what the model considers at the optimization phase, and what the actual results are if the original residual demand curves were used to compute the prices, is also different for both approaches. In this sense, the accuracy of the proposed formulation is significantly higher in terms of the total profits: when computing the ex-post results the error is 0.02% ($100 \cdot (92.22 - 92.20)/92.20$) for the proposed formulation and 4.47% ($100 \cdot (95.82 - 91.72)/91.72$) for the state-of-the-art approach that uses the income curve.

5.3. *Analysis of the model performance for different discretization steps*

As previously mentioned in Section 5.1, the proposed formulation implies a higher computational burden than the classical version. For this reason, four cases have been run to analyze the convenience of discretizing with greater or lesser precision taking into account the size of the resulting problem, the execution time and the level of detail obtained. Results for different discretization steps are shown in Table 4.

The discretization with a step of 0.05 €/MWh seems to be the most appropriate since it reduces the execution time by an order of magnitude compared to 0.01 €/MWh, and the difference in schedule is minimal. Thus, the following analyses will be carried out with a precision of 0.05 €/MWh.

Table 3
Model comparison with different Own_g and TxE_g, and maximum level of detail (180 seg and 0.01 €). Ex-post terms are calculated with the non-discretized original curves.

Model	Individual inc.	Portfolio inc.
Discretization	0.01 [€/MWh]	180 [seg]
Continuous var. n°	126 230	5089
Binary var. n°	25 793	5040
Resolution time [s]	276.6	52.0
Income optimized [k€]	1383.22	1378.39
Taxes optimized [k€]	270.26	265.77
Cost optimized [k€]	1020.75	1017.40
Profits optimized [k€]	92.22	95.82
Income ex-post [k€]	1383.20	1378.51
Taxes ex-post [k€]	270.26	269.39
Cost ex-post [k€]	1020.75	1017.40
Profits ex-post [k€]	92.20	91.72
OPTCR [%]	0.00	0.00
Energy sold [GWh]	23.93	23.94

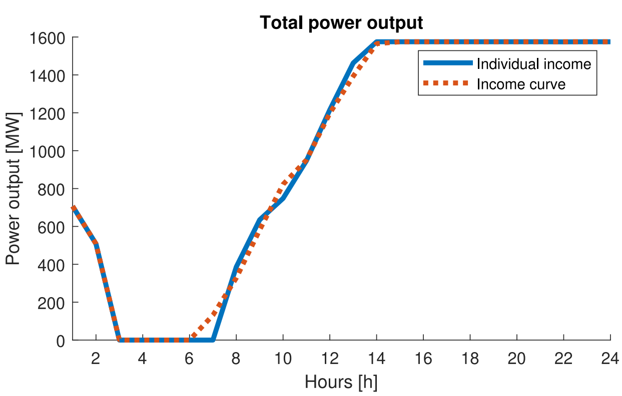

Fig. 7. Total generation for both models with different values of Own_g and TxE_g, and maximum level of detail (180 seg and 0.01 €).

Table 4
Cases with different discretization steps.

Discretization step [€/MWh]	0.01	0.05	0.10	0.50
Continuous var. n°	126 230	25 985	13 455	3440
Binary var. n°	25 793	5744	3238	1235
Resolution time [s]	276.6	37.2	14.6	6.7
Income optimized [k€]	1383.22	1383.09	1382.19	1401.35
Taxes optimized [k€]	270.26	270.21	270.00	273.77
Cost optimized [k€]	1020.75	1020.58	1019.78	1033.63
Profits optimized [k€]	92.22	92.30	92.41	93.95
Income ex-post [k€]	1383.20	1382.94	1381.65	1398.87
Taxes ex-post [k€]	270.26	270.21	269.98	273.65
Cost ex-post [k€]	1020.75	1020.58	1019.78	1033.63
Profits ex-post [k€]	92.20	92.16	91.89	91.59
OPTCR [%]	0.01	0.00	0.00	0.00
Energy sold [GWh]	23.93	23.93	23.91	24.30

5.4. Impact of differentiated income taxes

The proposed model is able to respond optimally to specific taxes applied individually to the generators whereas the portfolio income curve model does not have such sensitivity. To analyze in detail how the model would capture these changes, the following example is presented: Units G3 and G4 are technically identical but subject to three different tax schemes shown in Table 5.

With the tax scheme of case A the obtained schedule is the one shown in Fig. 8: G4 remains off all day whereas G3 starts-up at hour 8. The cost of generating with G3 is cheaper than what would be the cost of generating that same power output with G4. On the other hand,

Table 5
Generation cost for different taxes and prices.

Unit		TxI_g [%]	TxE_g [€/MWh]	TxI_g [k€]	TxE_g [k€]	Total [k€]
A	G3	4.00	1.00	12.839	5.367	18.206
	G4	1.00	3.00	3.210	16.101	19.311
B	G3	4.50	1.00	14.443	5.367	19.810
	G4	1.00	3.00	3.210	16.101	19.311

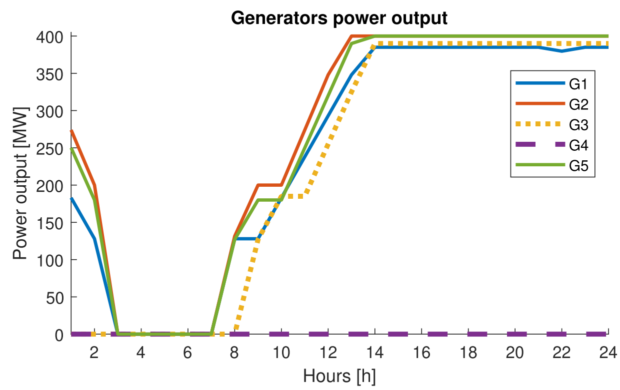

Fig. 8. Generation of the units for the 0.05 € discretization step case.

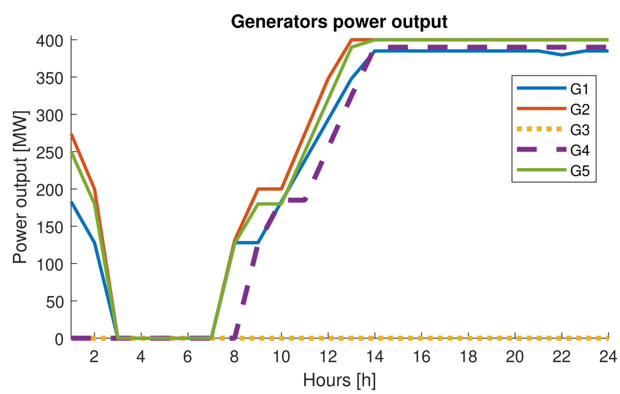

Fig. 9. Generation of the units for the 0.05 € discretization step case, and 0.045 p.u. tax for generation unit G3.

Fig. 9 shows what would result if the tax scheme is changed to case B. In this case, it can be seen that G4 is the unit that produces whereas G3 remains off during all day because now it is cheaper to use G4.

As expected, by raising the income tax to G3, its cost is higher than that of G4 and therefore it becomes better to generate with G4 instead.

5.5. Impact of CCS for different CO_2 taxes

A common approach found in the literature to assess the impact of technological developments in power systems is to simulate the operation of the system assuming a perfectly competitive market. Therefore, generation schedules can be simulated by means of a model where the system's operational costs are minimized. For instance, [25,26] assess the impact of CCS on the optimal expansion planning and on the short-term operation respectively assuming a minimum-cost criterion. However, in many electricity markets, the number of competitors is small, making it necessary to take into account the presence of strategic agents who make decisions with the aim of maximizing their market profits. In this example, the model has been run both with and without CCS for all generators at different CO_2 prices. It is important to note that possible changes in the offers of other competitors due to the

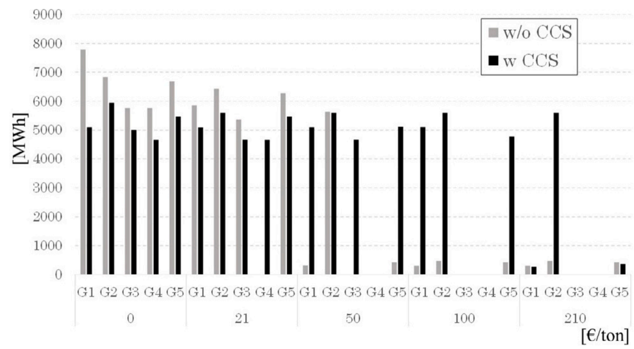

Fig. 10. Net output energy [MWh] with different values of $TxCO2$ = {0, 21, 50, 100, 210} €/ton with and without CCS.

change in CO_2 prices or their response to installing CCS have not been considered. Thus, the behavior of other competitors has been assumed to be fixed and represented by the same hourly residual demand functions as before.

Fig. 10 displays the daily net energy generated by each unit at different values of $TxCO2$ (ranging from 0 to 210 €/ton). The black and gray bars correspond to the cases with and without the installed CCS equipment, respectively. It can be seen that for price 0, the energy produced is lower with CCS for all the generators than without CCS due to the mentioned energy penalty. However, such behavior changes for higher prices as there are units not committed without CCS, that are started up with CCS because the lower emissions make them more competitive for higher CO_2 prices. Instead of a predefined load, the price-maker GenCo faces a family of hourly residual demand curves that gather the generation offers of its competitors and the bids submitted by all the buyers in the market. As a result, at higher CO_2 prices, the GenCo prefers to decrease its power output strategically to maximize its profit, and the rest of the agents balance such reduction automatically.

The hourly profiles of all the units are displayed in Fig. 11 without and with CCS (left and right, respectively, for all the considered CO_2 prices). Notice that the utilization of each group is not the same due to their different techno-economical characteristics. For instance, as group G2 has the lowest marginal heat rate, it is the last unit that is not committed when carbon prices increase (price equal to 50 €/ton without CCS, and price equal to 210 €/ton with CCS). In contrast, groups G3 and G4 have the highest variable cost; therefore, they are the first ones not committed when the carbon price increases. Explaining the output power values of each group at each hour is not straightforward, as these values are derived from the optimization model that considers the complex cost structure of each generator, all their technical constraints, and the factors that impact the resulting market incomes and taxes. It can be seen that for 0 €/ton it is more profitable to shut down G1 and start it up a few hours later respecting the start-up and shutdown trajectories just when CCS is implemented. For 21 €/ton, starting up unit G4 only becomes profitable with CCS. The reduction of the net output power due to the energy penalty increases the prices given the non-decreasing shape of the residual demand curves, and therefore although without CCS connecting such unit was not economically efficient, with CCS the objective function improves with its commitment. This pattern can be observed for higher CO_2, where even with a price of 210 €/ton, the case with CCS commits unit G2. Notice that the initial status of G1, G2, and G5 forces some production during the first two hours until they are off.

The corresponding CO_2 emissions are shown in Table 6. For the considered values of $TxCO2$ = {0, 21, 50, 210} the total emissions are

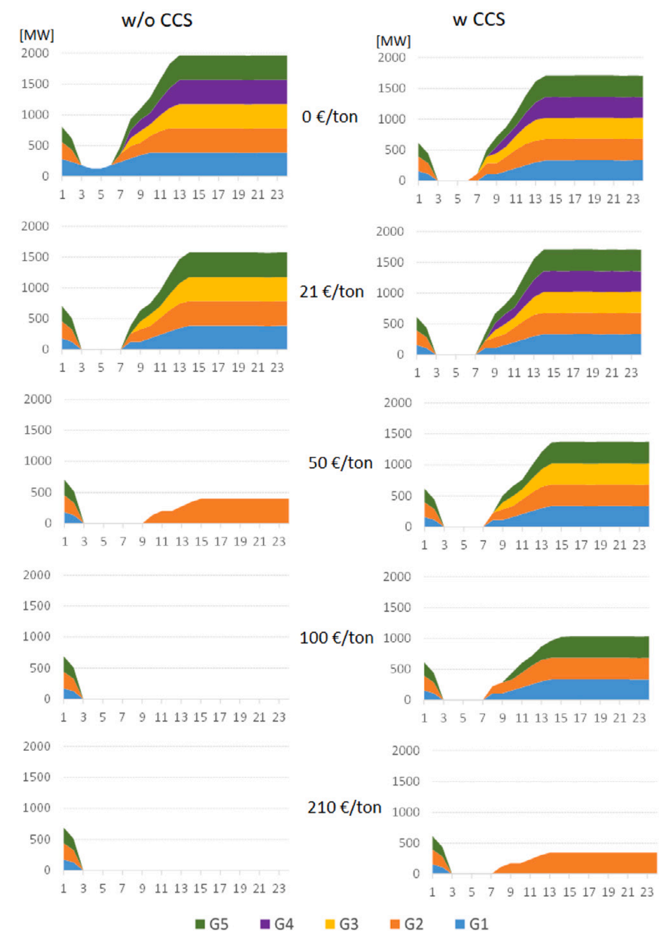

Fig. 11. Hourly scheduling with different values of $TxCO2$ = {0, 21, 50, 100, 210} €/ton with and without CCS.

reduced 90.76%, 87.66%, 61.70%, and 52.83% respectively. However, for the CO_2 price equal to 100 €/ton, the total emissions of this particular GenCo increase 20.40% as without CCS the model prefers to shutdown the initially committed units, while with CCS, it is more profitable to start-up three of the five available units.

5.6. Stochastic case

In the previous examples, the model has been run for a single scenario, i.e. a deterministic approach, in order to illustrate more easily the advantages of the proposed model. However, from the perspective of a GenCo that operates in a real electricity market, the impact of the uncertainty cannot be neglected, even in the short-term self-UC problem. Therefore, the formulation presented in Section 4.1 accounts for such uncertainty through a two-stage stochastic formulation. The first-stage decisions, common to all scenarios, are the commitment of the generation units throughout the day. The second stage decisions, different in each scenario, are the power output of each unit and the associated costs and revenues. The elaboration of the corresponding offers to be submitted to the market is out of the scope of this paper.

A case with nine scenarios of equal probability has been run, and these scenarios have been built by adding a price variation (ranging ±12 €/MWh) to the deterministic input data. The results for this case are summarized in Table 7.

Fig. 12 shows the generation profiles of groups G3 and G4 for all nine scenarios. It can be seen that G3 is on 16 h -although with

Table 6
CO_2 emissions [ton] for each generator with different values of $TxCO2$ = {0, 21, 50, 100, 210} [€/ton] with and without CCS.

$TxCO2$	Group	w/o CCS	w CCS
0		**12 109.0**	**1118.7**
	G1	2812.3	218.7
	G2	2319.8	232.0
	G3	2222.4	222.2
	G4	2222.4	207.3
	G5	2532.0	238.5
21		**8837.0**	**1090.5**
	G1	2189.8	218.5
	G2	2187.8	218.8
	G3	2074.6	207.5
	G4	0	207.3
	G5	2384.8	238.5
50		**2268.6**	**868.8**
	G1	143.9	218.9
	G2	1923.6	218.8
	G3	0	207.5
	G4	0	0
	G5	201.1	223.8
100		**537.23**	**646.8**
	G1	142.0	219.0
	G2	194.1	218.8
	G3	0	0
	G4	0	0
	G5	201.1	209.0
210		**537.2**	**253.4**
	G1	142.0	14.5
	G2	194.1	218.8
	G3	0	0
	G4	0	0
	G5	201.1	20.1

Table 7
Expected values for the stochastic solution.

	Optimized	$Ex-post$
Discretization step [€/MWh]	0.05	–
Continuous var. n°	99 712	–
Binary var. n°	19 107	–
Resolution time [s]	12 600	–
Income [k€]	1374.56	1374.39
Taxes [k€]	268.37	268.37
Cost [k€]	1013.53	1013.53
Profits [k€]	92.66	92.49
OPTCR [%]	2.06	–
Energy sold [GWh]	23.73	–

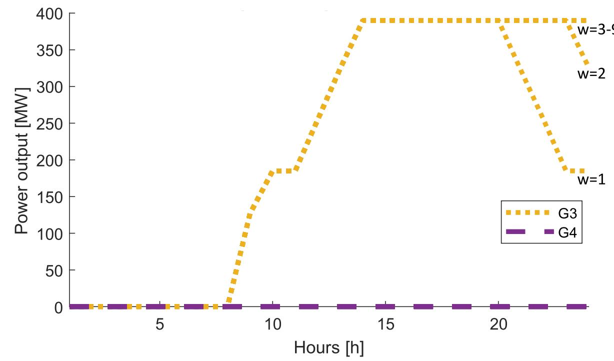

Fig. 12. Power generation of units G3 and G4 for all scenarios.

different load levels according to the scenarios- whereas G4 remains off the whole day. Group G3 is cheaper in most scenarios due to the tax scheme, and only in the scenarios with higher prices do the taxes change the cost enough to make G4 more profitable. Therefore, as this is a common decision for all scenarios, G4 remains off, and the units' commitment is unchanged.

6. Conclusion

The main conclusion that can be drawn from this research is the importance of representing in an accurate manner the different taxes that affect the operational costs incurred by a GenCo and the incomes obtained by the generators with shared ownership. Both issues are quite common in many real systems, and as shown in the paper, neglecting them can lead to inaccurate results. A deterministic model is first used to illustrate this finding, supported by several examples. In addition, a detailed stochastic optimization model is presented. In both cases, the individual market income of each generator is modeled using the binary expansion technique, and the accuracy of the obtained results for different discretization steps has also been analyzed. The proposed method overcomes the inability of state-of-the-art models to consider differentiated income taxes or shared ownership of generation units in the case of price-maker agents, and the study case shows its application to a realistic setting with satisfactory results. In particular, the impact of equipping the CCGT fleet with CCS has been analyzed to illustrate how the proposed model can be used to assess CO_2 emissions in the context of oligopolistic electricity markets.

Nomenclature

The amount of gas is modeled in terms of its equivalent thermal energy content (subscript t: MWh_t). Sets and variables start in lowercase and parameters in uppercase. The duration of each time period is one hour, and for clarity, it has been omitted in the equations. Subscript w indicates the dependence on a scenario for variables, parameters, and subsets.

Indexes and sets

$w \in W$	Scenarios {1 to W}.
$g \in G$	Generation units {1 to G}.
$G^{ccs} \subseteq G$	Subset of generation units with Carbon Capture and Sequestration.
$t, tt \in T$	Hourly time periods {1 to T}.
$d \in D$	Days {1 to D}.
$su \in SU$	Start-up type {1 (hottest) to SU (coldest)}.
$tu \in TU_g$	Hourly time periods of the start-up trajectories {1 to TU_g}.
$td \in TD_g$	Hourly time periods of the shut-down trajectories {1 to TD_g}.
$s \in S$	Income curve segments {1 to S}.
$c \in C$	Income curve concave intervals {1 to C}.
$i \in I$	Residual demand curve segments {1 to I}.
$\Omega^{cs}_{w,t}$	Existing combinations of segments s and concave interval c in each hour t for each scenario w.
$\Omega^{s}_{w,t}$	Existing segments s in each hour t for each scenario w.

Variables

$qI_{w,s,t}$	Energy in each segment s of the income curve at hour t [MWh].
$qbinI_{w,c,t}$	Activation variable of each income curve concave intervals c at hour t {0,1}.
$rT_{w,t}$	Total revenue at hour t [€].
$a_{w,i,t}$	Activation variable of each residual demand curve segment i at hour t {0,1}.
$k_{w,i,g,t}$	$pt_{g,t}$ when $a_{i,t}$ is active and 0 otherwise [MW].
$rG_{w,g,t}$	Revenue for each generator g at hour t [€].
$csG_{w,g,t}$	Total cost of generator g at hour t [€].
$csCN_{w,g,t}$	Fuel cost of each generator g at hour t [€].
$cnG_{w,g,t}$	Fuel consumption of each generator g at hour t [MWh_t].
$csOM_{g,t}$	Operation and maintenance cost of each generator g at hour t [€].
$txG_{w,g,t}$	Total tax of generator g at hour t [€].
$txE_{w,g,t}$	Generation tax per energy produced of generator g at hour t [€].
$txI_{w,g,t}$	Generation tax per income of generator g at hour t [€].
$txCN_{w,g,t}$	Fuel tax of generator g at hour t [€].
$tx\mathrm{CO2}_{w,g,t}$	CO_2 tax of generator g at hour t [€].
$p_{w,g,t}$	Power generated over $\underline{P}_g$ by generator g at hour t [MW].
$pt_{w,g,t}$	Total power generated by generator g at hour t [MW].
$v_{g,t}$	Commitment status of generator g at hour t {0,1}.
$y_{g,t}$	Start-up decision of generator g at hour t {0,1}.
$z_{g,t}$	Shut-down decision of generator g at hour t {0,1}.
$\delta_{g,su,t}$	Start-up decision of generator g at hour t for each start-up type su {0,1}.

Parameters

$Prob_w$	Probability of each scenario w [p.u.].
$\underline{Iq}_{w,s,t}$	Minimum energy of each income curve segment s at hour t [MWh].
$\overline{Iq}_{w,s,t}$	Maximum energy of each income curve segment s at hour t [MWh].
$Islp_{w,s,t}$	Slope of each income curve segment s at hour t [€/MWh].
$\Pi_{w,i,t}$	Price of each residual demand curve segment i at hour t [€/MWh].
$\underline{\Pi q}_{w,i,t}$	Minimum energy of each residual demand curve segment i at hour t [MWh].
$\overline{\Pi q}_{w,i,t}$	Maximum energy of each residual demand curve segment i at hour t [MWh].
Own_g	Percentage of ownership of generator g [p.u.].
$CNmn_g$	Fuel consumption at $\underline{P}_g$ of generator g [MWh_t/h].
$CNvr_g$	Variable fuel consumption of generator g over $\underline{P}_g$ [MWh_t/MWh].
$CNsu_{g,su}$	Start-up fuel consumption of generator g for start-up type su [MWh_t].
$CNsd_{gts}$	Shut-down fuel consumption of generator g [MWh_t].
$\overline{P}_g$	Maximum power output of generator g [MW].
$\underline{P}_g$	Minimum power output of generator g [MW].
$TmnS_{g,su}$	Minimum downtime of generator g for each start-up type su [h].
IS_g	Initial commitment status of generator g {0,1}.
IP_g	Initial power output over $\underline{P}_g$ of generator g [MW].
TUo_g	Time that generator g has been on before the optimization period [h].
TDo_g	Time that generator g has been down before the optimization period [h].
$TmnOff_g$	Minimum downtime of generator g [h].
$TmnOn_g$	Minimum uptime of generator g [h].
RU_g	Ramp-up rate of generator g [MW/h].
RD_g	Ramp-down rate of generator g [MW/h].
TU_g	Start-up time of generator g [h].
TD_g	Shut-down time of generator g [h].
$PU_{g,tu}$	Power output during start-up of generator g at period tu of the shutdown trajectory [MW].
$PD_{g,td}$	Power output during shut-down of generator g at period td of the shutdown trajectory [MW].
OMh_g	Operation and maintenance cost of generator g for each hour [€/h].
$OMsu_g$	Operation and maintenance cost of generator g for each start-up [€/su].
TxE_g	Generation tax per energy produced [€/MWh].
TxI_g	Generation tax per income [p.u.].
TxC	Generation tax per income common to all generation units [p.u.].
$TxCN_g$	Fuel tax [€/MWh_t].
$Tx\mathrm{CO2}$	CO_2 tax [€/ton].
$\mathrm{CO2}r_g$	CO_2 emission ratio [ton/MWh_t].
PCN_g	Fuel price [€/MWh_t].
ρ_g^{ep}	Energy penalty factor that decreases output net power of generator $g \in G^{ccs}$ [p.u.].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The authors would like to thank Dr. Jose Portela González for his helpful assistance regarding the generation of the residual demand curves for the case study.

Appendix. Self-UC formulation

This appendix includes all the equations of self-UC model that are not related to the income calculation presented previously in Section 4. These equations are in common with previous work published by these authors [27]. All the time periods are considered hourly periods and omitted for clarity purposes.

Total power output of the units.

$$pt_{w,g,t} = \sum_{tu \in TU_g} \left[PU_{g,tu} \cdot y_{g,t+TU_g+1-tu} \right] + \sum_{td \in TD_g} \left[PD_{g,td} \cdot z_{g,t+1-td} \right] + \underline{P}_g \cdot v_{g,t} + p_{w,g,t} \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{A.1}$$

Units are forced to stop at minimum power output.

$$IP_g \le \left(\overline{P}_g - \underline{P}_g \right) \left(IS_g - z_{g,t} \right) \quad \forall g \in G, t \in \{1\} \tag{A.2a}$$

$$p_{w,g,t-1} \le \left(\overline{P}_g - \underline{P}_g \right) \left(v_{g,t-1} - z_{g,t} \right) \quad \forall w \in W, \forall g \in G, \forall t \in T - \{1\} \tag{A.2b}$$

Units are forced to start at minimum power output.

$$p_{w,g,t} \leq \left(\overline{P}_g - \underline{P}_g\right)\left(v_{g,t} - y_{g,t}\right) \quad \forall w \in W, \forall g \in G, \forall t \in T \tag{A.3}$$

Commitment status, start-ups and shut-downs coherence.

$$y_{g,t} - v_{g,t} - z_{g,t} + IS_g = 0 \quad \forall g \in G, \forall t \in \{1\} \tag{A.4a}$$

$$y_{g,t} - v_{g,t} - z_{g,t} + v_{g,t-1} = 0 \quad \forall g \in G, \forall t \in T - \{1\} \tag{A.4b}$$

Minimum on-time of the units.

$$\sum_{\substack{tt \in T \\ t - TmnOn_g < tt \leq t}} \left[y_{g,tt}\right] + IS_g \leq v_{g,t} \quad \forall g \in G, \forall t \in T \mid t \leq TmnOn_g - TUo_g \tag{A.5a}$$

$$\sum_{\substack{tt \in T \\ t - TmnOn_g < tt \leq t}} \left[y_{g,tt}\right] \leq v_{g,t} \quad \forall g \in G, \forall t \in T \mid t > TmnOn_g - TUo_g \tag{A.5b}$$

Minimum off-time of the units.

$$\sum_{\substack{tt \in T \\ t - TmnOff_g < tt \leq t}} \left[z_{g,tt}\right] + \left(1 - IS_g\right) \leq 1 - v_{g,t} \quad \forall g \in G, \forall t \in T \mid t \leq TmnOff_g - TDo_g \tag{A.6a}$$

$$\sum_{\substack{tt \in T \\ t - TmnOff_g < tt \leq t}} \left[z_{g,tt}\right] \leq 1 - v_{g,t} \quad \forall g \in G, \forall t \in T \mid t > TmnOff_g - TDo_g \tag{A.6b}$$

Maximum decrease in unit power output.

$$IP_g - p_{w,g,t} \leq RD_g\left(v_{g,t} + z_{g,t}\right) \quad \forall w \in W, \forall g \in G, t \in \{1\} \tag{A.7a}$$

$$p_{w,g,t-1} - p_{w,g,t} \leq RD_g\left(v_{g,t} + z_{g,t}\right) \quad \forall w \in W, \forall g \in G, \forall t \in T - \{1\} \tag{A.7b}$$

Maximum increase in unit power output.

$$p_{w,g,t} - IP_g \leq RU_g \cdot v_{g,t} \quad \forall w \in W, \forall g \in G, \forall t \in \{1\} \tag{A.8a}$$

$$p_{w,g,t} - p_{w,g,t-1} \leq RU_g \cdot v_{g,t} \quad \forall w \in W, \forall g \in G, \forall t \in T - \{1\} \tag{A.8b}$$

Relation between start-up type and number of hours off.

$$\delta_{g,t,su} \leq \sum_{\substack{tt \in T \\ tt > t - TmnS_{g,su+1} \\ tt \leq t - TmnS_{g,su}}} \left[z_{g,tt}\right] \quad \forall g \in G, \forall su \in SU, \forall t \in T \mid t \geq TmnS_{g,su+1} - TDo_g \tag{A.9}$$

Relation between type of start-up and start-up decision.

$$\sum_{su \in SU} \left[\delta_{g,t,su}\right] = y_{g,t} \quad \forall g \in G, \forall t \in T \tag{A.10}$$

References

[1] Newbery DM. Why tax energy? Towards a more rational policy. Energy J 2005;26(3):1–39.

[2] Sijm J, Neuhoff K, Chen Y. CO_2 cost pass-through and windfall profits in the power sector. Climate Policy 2006;6:49–72.

[3] Simoglou CK, Biskas PN, Bakirtzis AG. Optimal self-scheduling of a thermal producer in short-term electricity markets by milp. IEEE Trans on Power Systems 2010;25(4):1965–77. http://dx.doi.org/10.1109/TPWRS.2010.2050011.

[4] García-González J, Barquin J. Self-unit commitment of thermal units in a competitive electricity market. In: 2000 Power Engineering Society Summer Meeting (Cat. No.00CH37134), vol. 4. 2000, p. 2278–83.

[5] de la Torre S, Arroyo J, Conejo A, Contreras J. Price maker self-scheduling in a pool-based electricity market: a mixed-integer LP approach. IEEE Trans on Power Systems 2002;17(4):1037–42.

[6] Simoglou CK, Biskas PN, Bakirtzis AG. Optimal self-scheduling of a dominant power company in electricity markets. Int J Electr Power Energy Syst 2012;43(1):640–9, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061512002281.

[7] Baíllo Á, Ventosa M, Ramos A, Rivier M. Strategic unit commitment for generation companies in deregulated electricity markets. Boston: Kluwer Academic Publishers; 2001.

[8] Baíllo Á, Ventosa M, Rivier M, Ramos A. Optimal offering strategies for generation companies operating in electricity spot markets. IEEE Trans on Power Systems 2004;19(2):745–53.

[9] Cerisola S, Baíllo Á, Fernández-López JM, Ramos A, Gollmer R. Stochastic power generation unit commitment in electricity markets: A novel formulation and a comparison of solution methods. Oper Res 2009;57(1):32–46.

[10] Pelagatti M. Supply Function Prediction in Electricity Auctions. Milano: Springer Milan; 2013, p. 203–13.

[11] Soares RA, Saraiva JT, Fidalgo JN, Martins BC. Forecast of the bidding curve of generation players in the iberian electricity market. In: 2015 12th International conference on the European Energy Market (EEM). 2015, p. 1–5.

[12] Vázquez S, Rodilla P, Batlle C. Residual demand models for strategic bidding in European power exchanges: Revisiting the methodology in the presence of a large penetration of renewables. Electr Power Syst Res 2014;108:178–84.

[13] Portela González J, Muñoz San Roque A, Sánchez-Úbeda EF, García-González J, González Hombrados R. Residual demand curves for modeling the effect of complex offering conditions on day-ahead electricity markets. IEEE Trans on Power Systems 2017;32(1):50–61.

[14] Bakirtzis AG, Ziogos NP, Tellidou AC, Bakirtzis GA. Electricity producer offering strategies in day-ahead energy market with step-wise offers. IEEE Trans on Power Systems 2007;22(4):1804–18.

[15] Barroso L, Carneiro R, Granville S, Pereira M, Fampa M. Nash equilibrium in strategic bidding: a binary expansion approach. IEEE Trans on Power Systems 2006;21(2):629–38.

[16] Kazempour J, Hobbs BF. Value of flexible resources, virtual bidding, and self-scheduling in two-settlement electricity markets with wind generation—Part I: Principles and competitive model. IEEE Trans on Power Systems 2018;33(1):749–59.

[17] Kazempour J, Hobbs BF. Value of flexible resources, virtual bidding, and self-scheduling in two-settlement electricity markets with wind generation—Part II: ISO models and application. IEEE Trans on Power Systems 2018;33(1):760–70.

[18] Sánchez-Úbeda EF, Wehenkel L. The hinges model: a one-dimensional continuous piecewise polynomial model. In: Information processing and management of uncertainty in knowledge-based systems, IPMU'1998 1998, París, Francia, july. 1998.

[19] Metz B, Davidson O, de Coninck H, Loos M, Meyer L. IPCC Special Report on Carbon dioxide capture and storage. Tech. Rep., Cambridge University Press; 2005.

[20] European Commission's Joint Research Centre (JRC). Reference document on best available techniques for large combustion plants. Tech. Rep., Brussels, Belgium: European Union; 2012, [Online]. Available: https://ec.europa.eu/jrc/en/publication/eur-25244-en.

[21] Agency IE. Energy technology perspectives. Paris, France: IEA; 2017.

[22] Bandyopadhyay R, Patiño-Echeverri D. Alternative energy storage for wind power: Coal plants with amine-based ccs. Energy Procedia 2014.

[23] Vaccarelli M, Carapellucci R, Giordano L. Energy and economic analysis of the CO2 capture from flue gas of combined cycle power plants. Energy Procedia 2014;45:1165–74, ATI 2013 - 68th Conference of the Italian Thermal Machines Engineering Association. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1876610214001234.

[24] Otaola-Arca P. Case study data chapter 4. 2022, [Online]. Available: https://zenodo.org/record/6375669.

[25] Saboori H, Hemmati R. Considering carbon capture and storage in electricity generation expansion planning. IEEE Trans Sustain Energy 2016;7(4):1371–8.

[26] Zhang R, Yan K, Li G, Jiang T, Li X, Chen H. Privacy-preserving decentralized power system economic dispatch considering carbon capture power plants and carbon emission trading scheme via over-relaxed ADMM. Int J Electr Power Energy Syst 2020;121:106094, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061520300132.

[27] Otaola-Arca P, García-González J, Marino F, Rivera I. Modeling of third party access tariffs and portfolio gas purchases of CCGTs in the self-unit commitment problem. IEEE Trans on Power Systems 2021;36(4):2771–85.