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Modeling of Third Party Access Tariffs and Portfolio Gas Purchases of CCGTs in the Self-Unit Commitment Problem

Pedro Otaola-Arca, Javier García-González, Fernando Mariño, and Ignacio Rivera

***Abstract*—The structure of the operational costs of gas fired units (GFU) in real power systems is much more complex than what standard unit-commitment (UC) models consider in the state-of-the-art formulations. On the one hand, when a generation company owning several GFUs procures its gas -either totally or partially- at the gas spot market, the final fuel price will depend on the total gas purchases. This fact couples the operation of all the GFUs as it is impossible to build individual cost functions for each generator. On the other hand, as any other gas consumer, the generation company has to pay the gas Third Party Access (TPA) tariffs. The generation company must contract in advance the monthly TPA capacity for each gas exit point and depending on such decision, the final variable cost of the GFUs will be different. This paper states the importance of modeling properly both issues and presents a novel mathematical formulation that can be embedded in a self-UC model. The presented example case highlights the benefits of the proposed formulation.**

***Index Terms*—CCGT, electricity market, gas market, profit maximization, third party access (TPA), unit commitment (UC).**

NOMENCLATURE

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

A. Sets

$g \in G$	generators [1 to G].
$t, tt \in T$	hourly time periods [1 to T].
$su \in SU$	start-up type [1 (hottest) to SU (coldest)].
$x \in X$	exit points of the gas network [1 to X].
$d \in D$	gas days [1 to D].
$m \in M$	gas months [1 to M].
Ω_d^t	hours t belonging to days d.
Ω_m^d	days d belonging to months m.
m_d	month m to which the day d belongs.
$tu \in TU_g$	hourly time periods of the start-up trajectories.
$td \in TD_g$	hourly time periods of the shut-down trajectories.
$b \in B$	gas blocks [1 to B].
$\omega \in \Omega$	scenarios [1 to Ω].
$S_\omega^t \subseteq \Omega$	subset of scenarios that are indistinguishable to scenario ω at stage t.
$S_\omega^d \subseteq \Omega$	subset of scenarios that are indistinguishable to scenario ω on day d.
$S_\omega^m \subseteq \Omega$	subset of scenarios that are indistinguishable to scenario ω in month m.

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B. Parameters

$\bar{P}_g$	maximum power output of generator g [MW].
$\underline{P}_g$	minimum power output of generator g [MW].
$CSmn_g$	generation cost at $\underline{P}_g$ of generator g [€/h].
$CSvr_g$	variable cost of generator g [€/MWh].
$CSsu_{g,su}$	start-up cost of generator g for start-up type su [€].
$CSsd_g$	shut-down cost of generator g [€].
$CNsu_{g,su}$	start-up gas consumption of generator g for start-up type su [$\mathrm{MWh_t}$].
$CNsd_g$	shut-down gas consumption of generator g [$\mathrm{MWh_t}$].
$CNmn_g$	gas consumption for power output $\underline{P}_g$ of generator g [$\mathrm{MWh_t}$/h].
$CNvr_g$	variable gas consumption of generator g [$\mathrm{MWh_t}$/MWh].
$Tp_{x,d}$	pre-contracted TPA capacity at exit point x on day d [$\mathrm{MWh_t}$/day].
$Tu_{x,m}$	price of pipeline usage at exit point x in month m [€/$\mathrm{MWh_t}$].
$Td_{x,m}$	daily capacity price at exit point x in month m [€/$\mathrm{MWh_t}$/day].
$Tm_{x,m}$	monthly capacity price at exit point x in month m [€/$\mathrm{MWh_t}$/day].
$\Pi_{t,\omega}^E$	hourly electricity marginal price at hour t [€/MWh].
$\Pi_{d,\omega}^G$	daily gas marginal price on day d [€/$\mathrm{MWh_t}$].
OMh_g	operation and maintenance cost of generator g for each hour [€/h].

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$OMsu_g$	operation and maintenance cost of generator g for each start-up [€/su].
$Avail$	initial available gas [MWh_t].
$Sd_{x,d}$	daily storage capacity price at point x on day d [€/MWh_t/day].
$Sm_{x,m}$	monthly storage capacity price at point x in month m [€/MWh_t/day].
$Sp_{x,d}$	pre-contracted storage capacity at point x on day d [MWh_t/day].
Si_x	injection cost to storage facility at point x [€/MWh_t].
Se_x	extraction cost from storage facility at point x [€/MWh_t].
$PCO2$	CO_2 price [€/ton].
$CO2r_g$	CO_2 emission ratio of generator g [ton/MWh_t].
$Qb_{d,b,\omega}$	gas quantity to buy on day d for block b [MWh_t].
$Qs_{d,b,\omega}$	gas quantity to sell on day d for block b [MWh_t].
$Pb_{d,b,\omega}$	gas market price to buy on day d for block b [€/MWh_t].
$Ps_{d,b,\omega}$	gas market price to sell on day d for block b [€/MWh_t].
$TmnS_{g,su}$	minimum downtime of generator g for each start-up type su [h].
TDo_g	time that generator g has been down before the optimization period [h].
IS_g	initial commitment status of generator g {0,1}.
RD_g	ramp-down rate of generator g [MW/h].
RU_g	ramp-up rate of generator g [MW/h].
$Prob_\omega$	probability of each scenario [p.u.].
$PSD_{g,td}$	power output during shut-down of generator g at time td of the shutdown trajectory [MW].
$PSU_{g,tu}$	power output during start-up of generator g at time td of the shutdown trajectory [MW].
TSD_g	shut-down time of generator g [h].
TSU_g	start-up time of generator g [h].
$TmnOn_g$	minimum uptime of generator g [h].
$TmnOff_g$	minimum downtime of generator g [h].

C. Variables

$\delta_{g,t,su,\omega}$	start-up decision of generator g at hour t for each type su{0,1}.
$y_{g,t,\omega}$	start-up decision of generator g at hour t {0,1}.
$v_{g,t,\omega}$	commitment status of generator g at hour t {0,1}.
$z_{g,t,\omega}$	shut-down decision of generator g at hour t {0,1}.
$p_{g,t,\omega}$	power generated over $\underline{P}_g$ by generator g at hour t [MWh].
$pt_{g,t,\omega}$	total power generated by generator g at hour t [MWh].
$csTot_\omega$	total cost of the generators [€].
$cnG_{g,t,\omega}$	gas consumption for each generator g at hour t [MWh_t].
$cnX_{x,d,\omega}$	gas consumption at exit point x on day d [MWh_t].
$dT_{x,d,\omega}$	daily TPA capacity at exit point x on day d [MWh_t].
$mT_{x,m,\omega}$	monthly TPA capacity at exit point x in month m [MWh_t].
$qa_{d,\omega}$	daily available gas on day d [MWh_t].
$qb_{d,\omega}$	gas purchases on day d [MWh_t].
$qb_{d,b,\omega}$	gas purchases on day d per block b [MWh_t].
$qs_{d,b,\omega}$	gas sales on day d per block b [MWh_t].
$dS_{x,m,\omega}$	daily storage capacity at point x in month m [MWh_t].
$mS_{x,m,\omega}$	monthly storage capacity at point x in month m [MWh_t].
$iS_{x,d,\omega}$	gas injection to storage facility at point x on day d [MWh_t].
$eS_{x,d,\omega}$	gas extraction from storage facility at point x on day d [MWh_t].
$csT_{x,m,\omega}$	TPA cost at point x in month m [€].
$csSup_{d,\omega}$	gas supply cost on day d [€].
$csS_{x,m,\omega}$	gas storage cost at point x in month m [€].
$csCO2_{g,t,\omega}$	CO_2 emissions cost of generator g at hour t [€].

I. Introduction

NATURAL gas fired units (GFUs), such as combined-cycle gas turbines (CCGTs), are expected to play an important role in the decarbonization process of the electricity sector during the following years. The strong interlinkage between the natural gas sector and the electric power industry requires a coordinated planning and operation of their related infrastructures [1], and a joint assessment of their market rules [2]. It is important to highlight that the gas sector is a network industry that requires an adequate tariff design, i.e. regulated costs, in order to recover the cost of building, operating, and maintaining the gas infrastructures such as pipelines, compression stations, regasification plants, etc. From the regulatory point of view, Third Party Access (TPA) policies have been and continue to be implemented worldwide (Australia, US, China, Malaysia, etc. [3]–[5]), and are one of the main pillars of the current EU energy market regulation [6]. The objective of TPA is to improve the market efficiency by forcing the owners of natural monopoly infrastructures to grant open and non-discriminatory access to third parties, fostering the competition among the agents [7].

Existing research works that consider explicitly the interdependence between the electricity and gas sectors can be categorized according to several characteristics. The first one is the time scope: the operational problem can range from a snap-shot analysis, typical for optimal power flow studies such as [8], [9], or [10], to a 24-hours period problem typical in unit commitment (UC) models as in [11] or [12], and to a whole year operation planning for medium-term hydro-thermal coordination models as [13] or medium-term models of coordinated power and gas systems as [14]. In [15] the authors present an optimization model for long-term gas contracts whereas [16] presents a realistic representation of how gas prices in spot markets are influenced by electricity generators consumption and its use for the profit maximization of power producers in the mid-term.

Another feature to classify existing models is whether they have been developed to support one agent to make its optimal decisions, i.e. *agent's perspective*, or if they have been

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developed under the *System Operator (SO) perspective*. The papers [17] and [13] belong to the group of *agent's perspective* models that also should include the so called self-UC which is the problem faced by a generation company (GENCO) who is responsible for finding the optimal scheduling of its generators trying to maximize the expected profit. In this self-UC model, operation and maintenance costs (O&M) and emission allowances must also be included. Special attention must be paid to the impact on the long-term maintenance contracts when CCGTs are combined with renewable energy sources as the flexibility provided by CCGTs might increase the number of start-ups and shutdowns, making those contracts more expensive, [18], [19].

The models under the *SO perspective* aim to perform the clearing of the gas and electricity markets in a more efficient manner by taking into account a more realistic representation of the physical constraints of the gas system as in [20] or [11]. In this sense, as the electricity market clearing must be robust against the presence of gas network contingencies, several authors have developed security constrained UC models adapted to the joint electricity and gas system as in [21], and [22]. Liu *et al*. [23] apply robust optimization to deal with demand and wind uncertainty assuming that natural gas flow through the pipelines can be approximated as a linear model. Finally, the models that try to simulate the behavior of rational agents that compete in both markets in order to have a better understanding of the potential interactions between the gas and electricity markets could be categorized as *market equilibrium* models as [24], [25] or [26]. These latter models can be used by regulators to assess the market functioning in the presence of strategic agents, or by market participants to make coordinated operations in the electricity and natural gas markets, [16].

Another important issue is the level of detail used to model the gas infrastructure. For instance, the stochastic optimization problem shown in [11] does not include a detailed representation of the natural gas-pipeline system assuming that committed units in the first-stage can respond to real-time natural gas availability unveiled in the second-stage. Other works such as [27] and [28] approximate the nonlinear natural gas flow equations by a set of linear constraints in terms of the pressure of the nodes, resulting in a mixed integer linear programming (MILP) problem, and [22] linearizes gas flow equations by an iterative method. Zhao *et al.* in [29] develop a market-based model that takes advantage of an iterative coordination mechanism that allows keeping the non-linear dynamic flow equations of the natural gas system. Manshadi and Khodayar [20] apply a sparse semi-definite programming (SDP) relaxation to optimize the operation of the electricity and natural gas networks, and Chen *et al.* in [12] present a UC model that integrates a second-order-cone relaxation of the non-linear and non-convex flow equations that consider pipeline line pack. It is worth to mention that some authors [24], [29], [30] highlight the importance of synchronizing the electricity and natural gas markets, which is not taken into account in the reviewed works.

Among all these reviewed research works, capacity contracting due to TPA tariffs is only considered in [17] and in [14], both of them focused on the medium-term and formulated as deterministic models: the first one co-optimizes the energy and reserve scheduling of a CCGT. In [14] the authors present a model to be used by a GENCO which buys gas in a spot market, contracts TPA capacity and participates in an electricity market. For the short-term self UC problem it is important to realize that these TPA tariffs must be paid by the CCGTs owners to be allowed to use natural gas, and therefore, these tariffs link the operation of all the CCGTs that withdraw gas from the same exit points. In addition, the fuel cost can be the result of procurement contracts signed with gas suppliers (normally in the long/medium term), or the resulting price of the short-term gas spot market. Therefore, the fact that the price of the fuel can depend on the total gas purchases of all the CCGTs introduces a set of complicating constraints that link the operation of all the units. This issue is neglected in all the previous works that consider as input data the cost functions of each generation unit in an individual manner.

In this context, the GENCO faces the problem of finding the optimal scheduling of its units while representing in an accurate manner the impact of the TPA tariffs, and the possible effect of portfolio gas purchases on the final operational costs. In addition, GENCOs need to determine how much monthly and daily capacity should be contracted (annually and quarterly contracting are out of the scope of short-term models). As these TPA payments depend on such monthly and daily capacities, the contracted capacities are decision variables that cannot be determined without considering at least a monthly time horizon.

One can conclude that current short-term models are not able to capture both the impact of TPA tariffs on the hourly optimal operation, and the possible impact on the purchased gas prices. This paper tries to overcome these drawbacks, and in particular it could be categorized under the group of *agent's perspective* models. The objective is to help a GENCO to find the optimal scheduling of its CCGTs taking into account a more realistic representation of the generation costs than the ones that can be found in the current literature.

To the authors' best knowledge, this paper is the first one that states the need to consider TPA and joint gas purchases in the gas spot market on the self-UC problem. Thus, the contributions can be summarized as follows:

- This paper provides a detailed mathematical formulation of the stochastic self-UC model including the TPA tariffs and portfolio gas purchases for different settings, and a comparison with the standard formulation is provided in order to highlight their importance. In addition, the presented models can help the GENCO to determine the TPA quantities (monthly and daily) that should be contracted taking into account the not-synchronized electricity and natural gas markets.
- The state-of-the-art modeling of start-up types found in the literature is not general and can fail for certain input parameters. This paper presents a refinement of such formulation that works well for any data set.

This paper is organized as follows. Section II describes the TPA regulation and highlights the problem faced by a GENCO in charge of operating some CCGTs. The mathematical for-

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mulation is shown in III, and the consideration of the initial conditions regarding start-up types is discussed in IV. Finally, the study case is presented in V and main conclusions are summarized in VI.

II. Third Party Access

A. Gas system description

As shown in Fig.1, the gas demand in a system can be supplied directly from internal gas fields or imported from other systems. Exports and imports can be done through international pipeline connections or by liquefied natural gas (LNG) carriers that are loaded at liquefaction plants and unloaded at regasification plants. Within the system, the gas moves through pressurized pipes and is delivered to customers at the exit points. Some of those gas consumers are the CCGTs that withdraw gas from the exit points (points A and B with 2 and 3 CCGTs connected respectively). In addition, gas storage facilities can be available to allow agents to store their gas by charging certain fees.

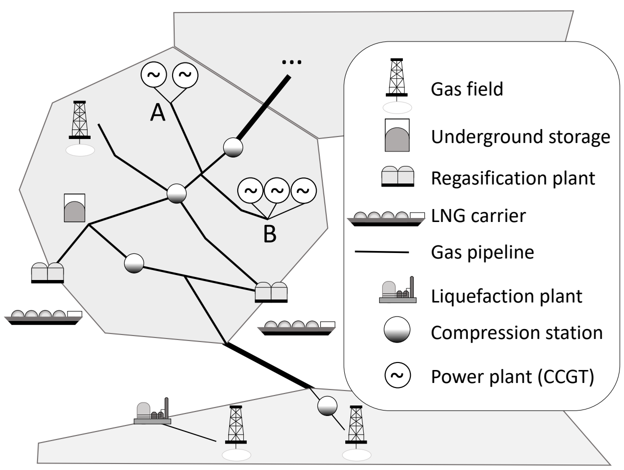

Fig. 1. Generic gas system schematic representation.

The natural gas system operator (SO) (there can be several SO responsible for different services or areas) is in charge of the maintenance and operation of this infrastructure. The SO has to recover its operating costs through the fees charged to the users of the system.

In the case of Europe, an internal market in natural gas (IMING) has been developing since 1999. For that matter, several regulations have been developed. In 2007 the European Commission emphasized the need for an integrated and competitive gas market within the Community [31]. Two years later, Regulation (EC) nº 715/2009 [6] established harmonized principles for network-access tariff calculation methodologies, capacity-allocation mechanisms, TPA services, congestion-management, balancing rules, and facilitation for capacity trading. This regulation also allowed to contract entry and exit services separately by establishing an entry-exit system for the transmission system of the IMING. In addition, the regulation obliged system operators to offer TPA services on a non-discriminatory basis, for long-term (>1 year) and short-term (<1 year) periods and to make information public regarding technical, contracted and available capacities for all relevant points.

B. TPA particularities in Europe

Commission Regulation (EU) 2017/459 of 16 March 2017 [32] establishes a network code on capacity allocation mechanisms in gas transmission systems. This regulation defined gas periods that do not coincide with natural calendar periods: gas years start on Oct. 31st and gas days start at 5:00 UTC during wintertime and 4:00 UTC during summertime. What is important about these gas periods is that they are not synchronized with the day-ahead electricity market. In addition, regarding capacity products, there are those with monthly duration, a temporary unit that is rarely used in UC or self-UC problems.

Commission Regulation (EU) 2017/460 [33] established a network code on harmonized transmission tariff structures for gas. It determined that operational costs of the gas network shall be recovered by the SO using capacity-based or commodity-based transmission tariffs. On one hand, capacity tariffs are based exclusively on cost drivers according to one of the following options: technical capacity, forecasted contracted capacity, technical capacity and distances, or forecasted contracted capacity and distances. On the other and, commodity tariffs are based on gas flow amounts or gas flow amounts and distances. Each national reference price methodology has to enable network users to reproduce reference price calculations, and when that reference price methodology is other than the capacity weighted distance reference price methodology (expressed in 1 and 2), the latter should serve as a counterfactual for comparison with the national methodology.

$$AD_{en}=\frac{\sum\limits_{ex}\left[CAP_{ex}\cdot D_{en\rightarrow ex}\right]}{\sum\limits_{ex}\left[CAP_{ex}\right]} \tag{1}$$

$$T_{en}=\frac{R_{Ten}\dfrac{CAP_{en}\cdot AD_{en}}{\sum_{en}\left[CAP_{en}\cdot AD_{en}\right]}}{CAP_{en}} \tag{2}$$

$en \in EN \subseteq X$ entry points.
$ex \in EX \subseteq X$ exit points.

AD_{en}	Weighted average distance for an entry point.
CAP_x	Forecasted contracted capacity at an entry/exit point.
$D_{en\rightarrow ex}$	Distance between the entry and exit point.
R_{Ten}	Part of the transmission services revenue to be recovered from capacity-based transmission tariffs at an entry point.
T_{en}	Reference price at an entry point.

For exit points, analogous parameters and equations can be defined by interchanging the subscripts en (entry) by ex (exit). Additionally, discounts can be applied to the calculated prices at entry/exit points from/to storage facilities or infrastructure developed to reduce the isolation of Member States. The reference prices are applied to yearly products and for non-yearly products (quarterly, monthly, daily or within-day) multipliers and seasonal factors may be applied. Reserve

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prices for interruptible capacity have discounts calculated according to Directive 2009/73/EC [34]. This means that as the methodology to compute those reference prices is public, the tariffs of the TPA used in this paper (daily and monthly) are considered input data where monthly tariffs are cheaper than daily ones.

C. Considerations for GENCOs

As previously reported by the authors in [35] the most important aspects that a GENCO participating in the electricity market must consider for its CCGTs scheduling in the short term, are the following ones: 1) the GENCO has to find the optimal TPA contracting strategy and include its related cost in the optimization; 2) time offset between TPA products and electricity day-ahead market; 3) TPA services have monthly and daily periods and therefore at least a whole month must be simulated; 4) TPA tariffs are deterministic input data parameters; 5) As the operation of the CCGTs depends on the total cost, the decisions about how much TPA should be contracted cannot be decoupled from the optimal hourly schedule problem.

Therefore, the decision-making process faced by the GENCO could be summarized as follows. Let assume that the GENCO is at the end of month 1 in Fig. 2. Notice that the end of the month is slightly displaced due to the mentioned time offset that affects gas products. At that stage, the GENCO must decide the capacity of monthly TPA for each exit point that should be contracted for the next month. This will enable the GENGO to withdraw from each exit point a given maximum daily quantity of gas during all the days that belong to month 2. However, this decision must be made under uncertainty. For instance, Fig. 2 illustrates such uncertainty by showing possible electricity price scenarios where darker colors correspond to a higher probability of occurrence (other random variables might also be present such as gas prices, failures, etc.). Once the monthly TPA contract has been established, as the days go by and the uncertainty is being unveiled, it may be that more or less gas is needed for a particular day. In the first case, the GENCO should participate in the daily TPA to contract the required extra capacity at a higher price. In the second case, for a specific day, it could seem that there is an excess of monthly TPA quantity. However, only a joint assessment of the entire month would allow to reach a correct conclusion, since the apparent unnecessary cost incurred for such day could be offset by the benefit of other days of the same month with higher consumption. In this sense, it is necessary to take into account the time. This situation fits very well in the framework of stochastic optimization, where the monthly TPA quantity is an example of "here and now" decision, whereas the daily TPA quantities are recourse decisions. Likewise, the hourly scheduling of the generation units can also be adapted during the month and except for the commitment status of the first day, they can be considered as recourse decisions.

Lets assume now that the GENGO is at the end of week 1 in Fig. 2. In that case, the monthly TPA for month 2 is no longer a decision variable, but an input parameter that must be taken into account when solving the optimal self-UC. For instance, if the time scope covered is exactly the same as shown in Fig. 2, the first two days of the optimization horizon belong to month 1, and therefore, their corresponding monthly TPAs are input parameters.

The problem of how to deal with the uncertainty in the UC problem has been studied extensively in the literature. The most used methodologies are the stochastic optimization, the robust optimization, and the chance-constrained optimization (see [36] for an updated review of these techniques). This paper applies multistage stochastic optimization, and therefore, the uncertainty is modeled by a scenario tree. This way, time-dependent variables are linked by nonanticipativity constraints to mimic the process followed by the GENCO when making its decisions under uncertainty, and imposing that monthly TPA quantities for the next month are first-stage decisions.

In addition, when facing uncertain outcomes, it is necessary to consider the level of risk aversion of the decision maker. The presented model is formulated as a risk-neutral problem. In case of being necessary to model other risk-aversion profiles, it would be possible to extend the model to define the conditional value at risk (CVaR) using its linear formulation [37], and to define the UC objective function as the mean-risk problem [38], i.e. a weighted sum of the mean value and the CVAr that allows to model different levels of risk aversion.

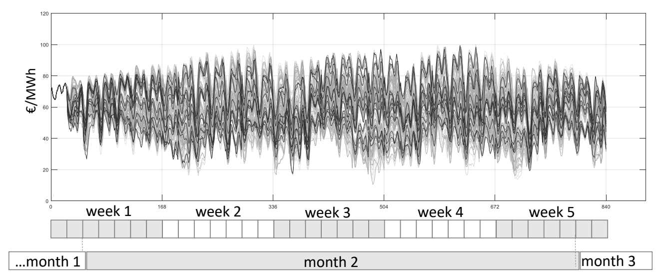

Fig. 2. Electricity price scenarios (darker color corresponds to a higher probability of occurrence).

III. Mathematical formulation

This section presents the mathematical formulation and defines the different models used to assess the impact of TPA tariffs and joint natural gas purchases. In this paper, the main model is formulated as a multistage stochastic MILP problem that can be solved directly when the size of the problem (mainly related to the number of generators and number of scenarios) is not very large. Otherwise, the model could be casted to benefit from decomposition techniques that have been applied to the multistage stochastic UC problem such as Benders decomposition [39], Danzig-Wolfe decomposition [40], Progressive Hedging [41], and stochastic dual dynamic integer programming [42]. In addition, the search procedure could be improved by applying the branch-and-fix coordination algorithm [43]. An extensive state-of-the-art review regarding stochastic UC recent developments can be found in [44].

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A. Assumptions

Energy deregulation varies by country and the liberalization process for the electricity and gas sectors can have different development speeds. In this paper it is assumed that a GENCO, owning several CCGTs, is in charge of planning the optimal scheduling of its units in a fully liberalized framework. In particular, the main assumptions can be summarized as follows:

- There is an electricity spot market. Only the sales on the day-ahead energy market have been considered for the sake of clarity. As it is not the main focus of this paper, although the GENCO could impact the electricity price with its operation, it is assumed that the GENCO acts as a price-taker in this electricity spot market. The reader is referred to [45] to extend the model for a price-maker case.
- There is a liquid gas spot market. For the case where the importance of arbitrage is highlighted (allowing the GENCO to use the purchased and stored gas to produce electricity or to sell it back in the market), it is assumed that the GENCO has a certain impact on the price of the natural gas.
- There is an entry-exit system, i.e., the users do not have to contract specific pathways within the gas network.
- The TPA tariffs couple the operation of the CCGTs that withdraw gas from the same exit point. A realistic TPA design has been considered where the daily/monthly capacity needs to be determined by the GENCO.

B. Discussion of the required equations

The model is a stochastic self-UC as it helps the GENCO to find the optimal UC and hourly scheduling of its own generators in a market environment under electricity and gas prices uncertainty.

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 appendix A.

The objective function of the model is to maximize the expected profit computed as the sum of all the hourly incomes in the electricity market, minus the total operational costs $csTot_\omega$ considering the probability of each scenario, (3):

$$max \left(\sum_{\omega \in \Omega} Prob_\omega \cdot \left[\sum_{t \in T} \left[\Pi^E_{t,\omega} \cdot \sum_{g \in G} [pt_{g,t,\omega}] \right] - csTot_\omega \right] \right) \quad (3)$$

In the standard self-UC formulation, the cost $csTot_\omega$ is computed by adding the individual cost functions of each generator as in (4):

$$csTot_\omega = \sum_{g \in G, t \in T} [CSmn_g \cdot v_{g,t,\omega} + CSvr_g \cdot p_{g,t,\omega}] + \sum_{g \in G, t \in T} \left[CSsd_g \cdot z_{g,t,\omega} + \sum_{su \in SU} [\delta_{g,t,su,\omega} \cdot CSsu_{g,su}] \right] \quad (4)$$

However, this formulation is unable to capture the complexity of the cost calculation of the CCGTs due to the TPA contracting and the joint gas purchases in the gas spot-market and other gas-related costs. For that reason, the proposed formulation substitutes (4) by (5)-(14). These new equations allow modeling the possibility of buying/selling gas in the spot market, a realistic representation of TPA contracting at each power plant exit point, and also the possibility to store gas. Notice that there is an offset between the gas and electricity days of six hours. In the following formulation all the days d and all the months m correspond to gas days and gas months respectively.

For network access and storage, it is considered that there are regulated tariffs for the following concepts:

- Network access at power plant exit points: a) capacity: daily/monthly usage capacity contracted (capacity for longer periods is predefined in parameter $Tp_{x,d}$); b) gas flow: payment for the real gas usage.
- Storage facilities: a) capacity: daily/monthly storage capacity contracted; b) gas flow: payment for gas injection (extraction) to (from) storage facilities.

For the gas acquisition, every day d and scenario ω is characterized by a given gas price $\Pi^G_{d,\omega}$. The amount of gas bought each day is represented by variable $qb_{d,\omega}$ that depends only on the day and scenario ω.

Equation (5) presents the total generation cost including: TPA, storage, gas supply, a fixed term regarding operation and maintenance (O&M) and CO_2 emissions cost. As this formulation disaggregates all the costs it is necessary to specify the O&M cost. The other four terms are computed in (6)-(9).

$$csTot_\omega = \sum_{m \in M} \left[\sum_{x \in X} [csT_{x,m,\omega} + csS_{x,m,\omega}] \right] + \sum_{d \in D} [csSup_{d,\omega}] + \sum_{g \in G, t \in T} [OMsu_g \cdot y_{g,t,\omega} + OMh_g \cdot v_{g,t,\omega} + csCO2_{g,t,\omega}] \quad (5)$$

TPA contracting cost at each power plant exit point (6) depends on the amount of daily and monthly capacity contracted and gas usage.

$$csT_{x,m,\omega} = \sum_{d \in \Omega^d_m} [cnX_{x,d,\omega} \cdot Tu_{x,m} + dT_{x,d,\omega} \cdot Td_{x,m}] + mT_{x,m} \cdot Tm_{x,m} \quad (6)$$

Gas supply cost (7) represents the cost of gas purchases.

$$csSup_{d,\omega} = \Pi^G_{d,\omega} \cdot qb_{d,\omega} \quad (7)$$

Storage cost (8) depends on capacity contracted at storage facilities plus injections and extractions to/from the facilities.

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$$csS_{x,m,\omega} = mS_{x,m} \cdot Sm_{x,m} + \sum_{d\in\Omega_m^d} [dS_{x,d,\omega} \cdot Sd_{x,m}] + \sum_{d\in\Omega_m^d} [iS_{x,d,\omega} \cdot Si_{x,m} + eS_{x,d,\omega} \cdot Se_{x,m}] \quad (8)$$

CO_2 cost (9) is expressed in terms of the gas consumption, the gas to CO_2 ratio, and CO_2 emissions price.

$$csCO2_{g,t,\omega} = cnG_{g,t,\omega} {\cdot} CO2r_g {\cdot} PCO2 \quad (9)$$

The following equations represent the technical constraints and relationships between variables used in the four cost equations that have been presented above.

Gas consumption at each exit point (11) is computed as the sum of the gas consumption of all the generators connected to that exit point (usually those which belong to the same power plant). Those individual consumptions of the generators (10) are calculated as a gas-to-power expression and the gas consumption of each start-up and shut-down.

$$cnG_{g,t,\omega} = CNmn_g {\cdot} v_{g,t,\omega} + CSvr_g {\cdot} p_{g,t,\omega} + \sum_{su\in SU} [CNsu_{g,su} \cdot \delta_{g,t,su,\omega}] + CNsd_g \cdot z_{g,t,\omega} \quad (10)$$

$$cnX_{x,d,\omega} = \sum_{g\in G, t\in\Omega_d^t} [cnG_{g,t,\omega}] \quad (11)$$

TPA capacity contracting must account for the exit point gas consumption (12) to ensure that the total contracted capacity (sum of the daily, monthly and pre-contracted ones) is respected by the obtained scheduling:

$$cnX_{x,d,\omega} \leq dT_{x,d,\omega} + mT_{x,m_d,\omega} + Tp_{x,d} \quad (12)$$

The daily/monthly storage capacity (13) that has to be contracted depends on the gas stored (available). Gas injections/extractions to/from storage facilities (14) depend on used and bought gas.

$$qa_{d,\omega} \leq \sum_{x\in X} [dS_{x,d,\omega} + mS_{x,m_d} + Sp_{x,d}] \quad (13)$$

$$qb_{d,\omega} = \sum_{x\in X} [cnX_{x,d,\omega} + iS_{x,d,\omega} - eS_{x,d,\omega}] \quad (14)$$

Gas purchases on the spot market (15) depend on the gas consumption and availability of stored gas.

$$\sum_{x\in X} [cnX_{x,d,\omega}] \leq qa_{d,\omega} + qb_{d,\omega} \quad (15)$$

Gas available for the following day (16) depends on the gas available for each day plus purchases minus gas consumption of the total portfolio. The gas available for the first simulation day (17) is input data to the model.

$$qa_{d+1,\omega} = qa_{d,\omega} - \sum_{x\in X} [cnX_{x,d,\omega}] + qb_{d,\omega} \quad (16)$$

$$qa_{d=1,\omega} = Avail \quad (17)$$

All the previous equations have been formulated by defining different decision variables for each scenario ω at each time stage t. In order to ensure that scenarios with a common history share the same decisions while they are indistinguishable, it is necessary to add the nonanticipativity constraint [46]. Let $x_{\omega,t}$ represent any of the decision variables presented in the previous formulation that depend on t and ω. Then the nonanticipativity constraint can be expressed as follows:

$$x_{t,\omega} = x_{t,\omega'} \ \forall t \in T, \forall \omega \in \Omega, \forall \omega' \in S_\omega^t \quad (18)$$

Where S_ω^t is the subset of scenarios that share the same history than scenario ω up to stage t.

However, as the time dependency is not restricted to hours, it is also necessary to apply a similar idea for the variables that depend on days d and months m. Following the same stylized formulation, the remaining nonanticipativity constraints can be written as follows:

$$x_{d,\omega} = x_{d,\omega'} \ \forall t \in T, \forall \omega \in \Omega, \forall \omega' \in S_\omega^d \quad (19)$$

$$x_{m,\omega} = x_{m,\omega'} \ \forall t \in T, \forall \omega \in \Omega, \forall \omega' \in S_\omega^m \quad (20)$$

For instance, for the time structure presented in Fig. 5 , the decision variable of how much monthly TPA capacity should be contracted in the second month at any exit point ($mT_{x,2,\omega}$) must be the same for all the scenarios.

C. Modeling the possibility of affecting the price in the gas market

When considering the possibility to buy gas and then sell it instead of using it for electricity generation, a certain impact on gas prices must be taken into account. This impact in prices has been modeled by monotonically increasing/decreasing step functions as in [47] in which each extra block of gas has a higher price when buying and lower price when selling. Fig. 3 illustrates these curves. For this model, the following equations (21)-(26) must replace equations (7),(14),(15) and (16), and the variable representing the purchased gas depends on the indexes day, scenario, and block ($qb_{d,b,\omega}$).

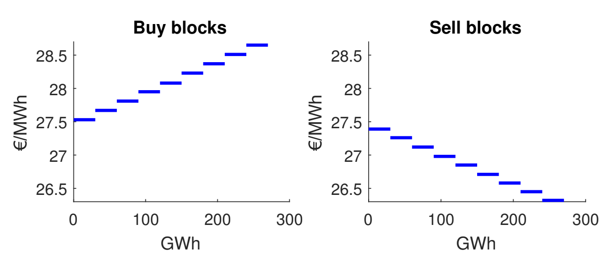

Fig. 3. Gas market price impact modeling for gas day 2.

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Gas supply cost (21) represents the cost of gas purchases minus the income of gas sales.

$$csSup_{d,\omega} = \sum_{b\in B} [qb_{d,b,\omega} \cdot Pb_{d,b,\omega} - qs_{d,b,\omega} \cdot Ps_{d,b,\omega}] \quad (21)$$

Gas injections/extractions to/from storage facilities (22) depend on used and traded gas.

$$\sum_{b\in B} [qb_{d,b,\omega} - qs_{d,b,\omega}] = \sum_{x\in X} [cnX_{x,d,\omega} + iS_{x,d,\omega} - eS_{x,d,\omega}] \quad (22)$$

Gas availability is computed for each day relating consumption, purchases and sales (23). Purchases and sales are limited to the quantities available in each step of the functions that define the gas prices (24)(25).

$$\sum_{x\in X} [cnX_{x,d,\omega}] \leq qa_{d,\omega} + \sum_{b} [qb_{d,b,\omega} - qs_{d,b,\omega}] \quad (23)$$

$$qb_{d,b,\omega} \leq Qb_{d,b,\omega} \quad (24)$$

$$qs_{d,b,\omega} \leq Qs_{d,b,\omega} \quad (25)$$

Gas available for the following day depends on the gas available for each day plus purchases, minus gas sales, minus gas consumption of the total portfolio (26).

$$qa_{d+1,\omega} = qa_{d,\omega} - \sum_{x\in X} [cnX_{x,d,\omega}] + \sum_{b\in B} [qb_{d,b,\omega} - qs_{d,b,\omega}] \quad (26)$$

D. Model definitions

Once the main equations have been explained, it is possible to define different versions of the stochastic self-UC problem under study to be able to compare their results, and thus analyze the relevance that a correct modeling of TPA tariffs and portfolio gas purchases can have. These models have been labeled as A, Bfix, B, and C :

A: model using the standard stochastic self-UC formulation that represents each generator's costs with a commitment cost and a variable cost. This model uses the following equations: (3), (4), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40) and (41).

Bfix: proposed model that represents generator's costs taking into account the need for contracting TPA and storage capacities and a fixed price for gas to supply the consumption of the units. This model uses the following equations: (3), (5), (6), (7), (8), (9), (10), (11), (12), (15), (16), (17), (13), (14), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40) and (41).

B: proposed model that represents generator's costs taking into account the need for contracting TPA and storage capacities and gas purchases in a gas spot market to supply the consumption of the units. The GENCO can impact gas market prices, and gas sales are not allowed. This model uses the following equations: (3), (5), (6), (21), (8), (9), (10), (11), (12), (15), (24), (16), (17), (13), (14), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40) and (41). The main difference with model Bfix regarding the used variables is that $qb_{d,\omega}$ depends on index b becoming $qb_{d,b,\omega}$. As the equations are the same as in the following model C the possibility to sell gas represented by the variable $qs_{d,b,\omega}$ is fixed to 0 in this case. Regarding equations, (7), (15), and (16) are substituted by (21), (23) and (26) to include possible sales to the market and the block dependency to $qb_{d,b,\omega}$. In addition, equations (24) and (25) are added to limit the amount of gas purchased/sold at each block price.

C: same model as B but allowing gas sales ($qs_{d,b,\omega} \geq 0$).

IV. Initial conditions for start-up types

The equations that determine the type of start-up according to the authors in [48] are (27) and in (28).

$$\delta_{g,t,su} \leq \sum_{tt=1+TmnS_{g,su}}^{TmnS_{g,su+1}} [z_{g,t-tt+1}] \qquad \begin{array}{ll} \forall t & \in [TmnS_{g,su+1}, T] \\ \forall su & \in [1, SU) \end{array} \quad (27)$$

$$\delta_{g,t,su} = 0 \qquad \begin{array}{ll} \forall t & \in (TmnS_{g,su+1} - TDo_g, TmnS_{g,su+1}) \\ \forall su & \in [1, SU) \end{array} \quad (28)$$

This formulation might not work properly when the discretization of start-up types considers only a few number of them, which is a common practice as it is necessary to keep the right balance between accuracy and complexity of the optimization model.

The data expressed in Table I and represented in Fig. 4 sets an example where the formulation does not work. This example shows a case where the type of the second start-up should be $\delta_{g,t=9,su=1} = 1$ but the formulation forces it to be $\delta_{g,t=9,su=1} = 0$ due to the condition $\delta_{g,t<12,su=1} = 0$ and therefore $\delta_{g,t=9,su=2} = 1$.

TABLE I
EXAMPLE DATA FOR INITIAL PERIODS.

TSU_g	1h	TSD_g	1h
IS_g	0 (off)	TDo_g	48h
$TmnOn_g$	4h	$TmnOff_g$	4h
$TmnSU_{g,su=1}$	4h	$TmnSU_{g,su=2}$	12h

It can be concluded that the formulation fails when the time required in the warmest start-up maneuver is larger than the time required to perform the following actions: to start-up; to be connected the minimum uptime; to shut-down, to be disconnected the minimum downtime, and to start-up a second time. Time steps between the different start-up types follow similar relations.

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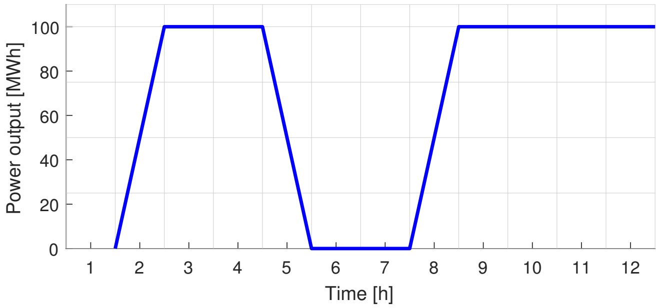

Fig. 4. Start-up during initial periods.

In order to ensure that the model works properly for any type of start-up data and initial conditions, an extension of the periods in which the constraint (27) should be applied is defined in (29), and (28) is no longer used.

$$\delta_{g,t,su} \leq \sum_{tt=1+TmnS_{g,su}}^{TmnS_{g,su+1}} [z_{g,t-tt+1}] \qquad \begin{array}{ll} \forall t & \in [TmnS_{g,su+1} - TDo_g, T] \\ \forall su & \in [1, SU) \end{array} \tag{29}$$

V. Case Study

The case example data consists of 6 CCGT units that have fictional but realistic characteristics shown in Table V (appendix B). These generation units are located at four exit-points, being together groups 1 and 2, and groups 5 and 6. The time horizon of the optimization is 841 hours that correspond to 5 weeks starting on September 29th, 2018 (this horizon includes one day with 25 hours due to the daylight saving time). TPA and storage data have been taken from the Spanish gas TSO Enagás [49] and is presented in Tables VI and VII (appendix B). CO_2 price (19.56€/t) has been taken from SENDECO2 [50]. Electricity and gas price scenarios are explained in subsection V-A.

The most intereseting comparisons are between models A and Bfix, and between models B and C. The first comparison highlights the difference between modeling units costs in a detailed manner versus using the standard approximated formulation. The second comparison ilustrates the importance of considering the possibility of arbitraging between markets, allowing the model to choose between selling gas back to the gas market or using it to produce and sell electricity to the market.

A. Scenario tree construction

In order to prepare the input data, the first step is to generate the scenarios of the random variables. Among the variety of possible approaches, Long Short-Term Memory (LSTM) [51] and Gated Recurrent Units (GRU) [52] are recurrent neural networks that allow to process and forecast complex times series data with multi-scale dynamics. In this case, a GRU has been implemented in Tensor Flow 2, with 100 neurons, and dropout of 0.1 during the training phase. The used explanatory variables are the Spanish inland electricity demand, the wind, hydro, nuclear and solar generation, and the France-Spain interconnection flow. Besides all those hourly values, the daily price at the Iberian gas market (MIBGAS, [53]) was added to the list of explanatory variables by replicating the daily price to all the corresponding hours of each day. After training the model, synthetic time series of gas price, wind, solar and hydro were sampled, and the GRU model was evaluated to a different combination of those series, resulting in a total number of 210 scenarios. Each one of those scenarios is a pair of electricity and gas time series that cover the considered 5-weeks horizon, and that can be characterized by a given probability.

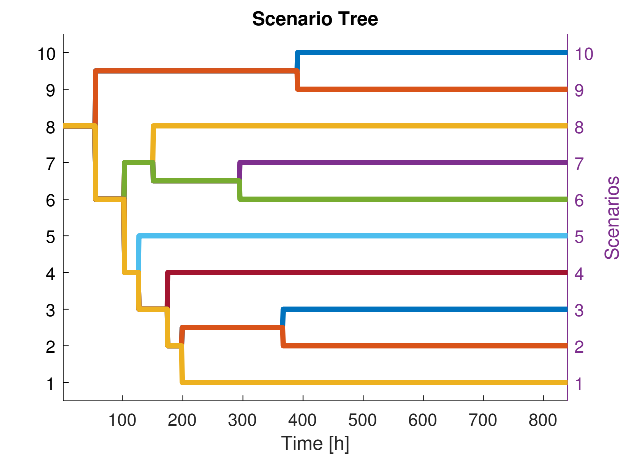

Fig. 5. Scenario tree.

Once the set of independent scenarios were obtained, the next step was to build the scenario tree by applying the scenario reduction technique presented in [54] and [55]. The total number of final scenarios was set to 10, and the branching was only allowed at the beginning of each day during the first three weeks. Fig. 5 shows the structure of the obtained tree, and Figs. 6 and 7 show the reduced scenarios of electricity and gas prices, respectively. The probability for the scenario 1 is 11.5%, 9.7% for scenario 2, 8.8% for scenario 3 and 10% for the remaining seven scenarios.

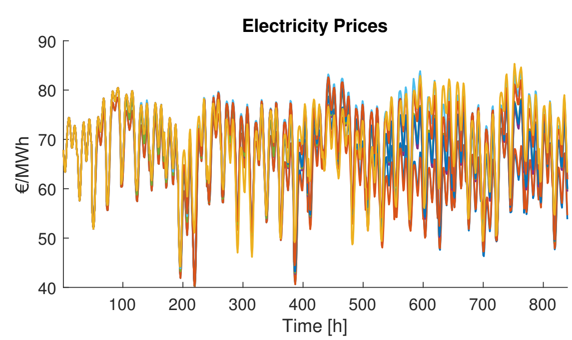

Fig. 6. Electricity day-ahead market prices for the scenario tree.

B. Models A vs Bfix

Appendix B details how the parameters $CSmn_g$, $CSvr_g$, $CSsd_g$ and $CSsu_{g,su}$ used to model the cost of the units in model A have been computed. By performing such calculation,

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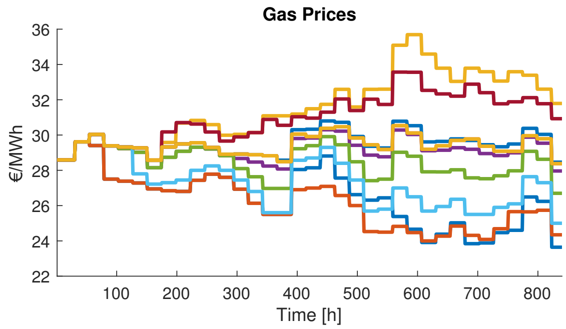

Fig. 7. Gas market prices for the scenario tree.

it is ensured that the parameters of model A represent in the most accurate manner the costs of the units for the optimal solution of this case example. This way, the comparison will be carried out with the most optimistic version of the standard model in order to establish a lower bound of the potential benefits of the proposed formulation.

Global results regarding total income, costs, profits and electricity generation for all the scenarios as well as for the stochastic solution are displayed in Table II. The values displayed for A are the ones that would result after computing the real cost considering the TPA tariffs and gas purchases that such scheduling would need. It can be checked that model Bfix obtains results that are approximately 12.93% better than model A for the stochastic solution.

The comparison between models A and Bfix can be enhanced by facing the obtained "here and now" decisions of the stochastic solutions to different scenarios. In particular, an out-of-sample analysis has been carried out by facing those decisions to the real prices of gas [53] and electricity [56] during the horizon under study. As shown in the rows labeled as "Real" in Table II, model Bfix obtains results that are 4.21% better than model A.

In order to compare the different hourly scheduling between models A and Bfix (considering model Bfix as the best solution when arbitrage is not allowed) the deviation between their electricity generation has been calculated using the formula in (30). The results show that model A has a difference in unit scheduling of 13.05% against model Bfix. In that formula, $pt^{M}_{g,t,\omega}$ represents the power output of each generator g in the hour t for the scenario ω as a result of the models Bfix and A.

$$\frac{100 \cdot \sum\limits_{\omega \in \Omega} \left[Prob_{\omega} \cdot \sum\limits_{g \in G, t \in T} \left[\frac{\left| pt^{Bfix}_{g,t,\omega} - pt^{A}_{g,t,\omega} \right|}{\overline{P_g}} \right] \right]}{n^{o}{}_{hours} \cdot n^{o}{}_{groups}} \tag{30}$$

Fig. 8 and 9 show in a graphical manner the scheduling of the 6 units when using the two models, for the scenarios where the scheduled power has the smallest and largest differences according to (30). Each row represents the hourly scheduling in a color scale where the darker the color, the higher the output power (i.e. white means being shutdown). It is observed that the two models have a general similar behavior producing more elecricity in scenario 5 which has higher electricity prices

TABLE II
GLOBAL RESULTS FOR MODELS A AND BFIX.

	Total cost [M€]	Total income [M€]	Total profits [M€]	Total electr. gen. [GWh]	Scenario
A	131.17	137.05	5.88	1974.09	1
	130.97	137.00	6.03	1970.36	2
	131.12	134.12	2.99	1969.41	3
	133.78	137.00	3.22	1970.36	4
	122.64	138.36	15.72	1968.80	5
	126.61	132.85	6.25	1961.60	6
	129.31	132.24	2.94	1963.31	7
	131.81	132.24	0.44	1963.31	8
	119.10	124.82	5.73	1955.65	9
	118.88	125.01	6.14	1947.12	10
	127.54	133.11	5.57	1964.47	Expected value
	118.11	125.95	7.84	1912.28	Real
Bfix	115.34	121.82	6.48	1722.14	1
	116.84	123.55	6.71	1750.96	2
	109.36	113.25	3.89	1633.90	3
	110.65	114.95	4.30	1620.25	4
	113.63	129.67	16.04	1830.52	5
	113.79	120.62	6.83	1762.25	6
	109.28	112.99	3.71	1651.34	7
	103.46	105.26	1.79	1528.97	8
	107.24	113.46	6.22	1768.90	9
	107.30	113.98	6.67	1766.37	10
	110.76	117.05	6.29	1704.53	Expected value
	109.91	118.07	8.17	1770.73	Real

and lower gas prices than scenario 8. Model A is not able to capture the real changes in cost due to the TPA tariffs, resulting in the units having considerably less decreases in load and shut-downs compared to model Bfix.

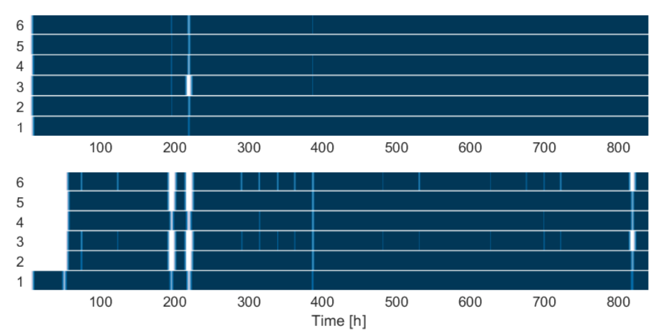

Fig. 8. CCGTs power output in scenario 5: models A (top) and Bfix (bottom).

Some small decreases in load for model Bfix can be appreciated in Figs. 8 and 9. To better understand the power output of the units and the reason for those changes, a more detailed representation is shown in Fig. 10. Hours included in the figure range from 505 to 583, including gas days 21st to 23rd and 6 hours of gas day 20th.

On the one hand, model A determines that producing at maximum power output during gas days 21st to 23rd is profitable. On the other hand, model Bfix takes into account TPA contracting. Consequently, the decision to produce during these three days depends also on the decisions regarding the scheduling of the whole month to determine the amount of monthly TPA capacity to be contracted. In this case, the model determined that the optimal monthly TPA capacity was 33.98

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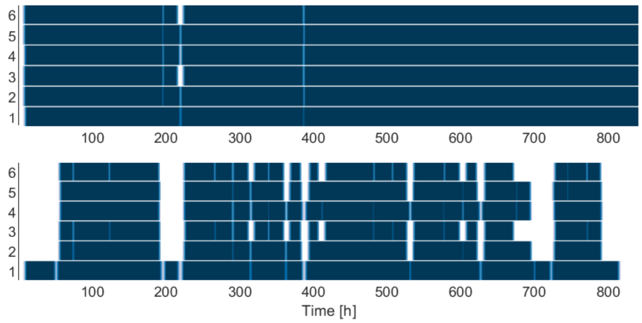

Fig. 9. CCGTs power output in scenario 8: models A (top) and Bfix (bottom).

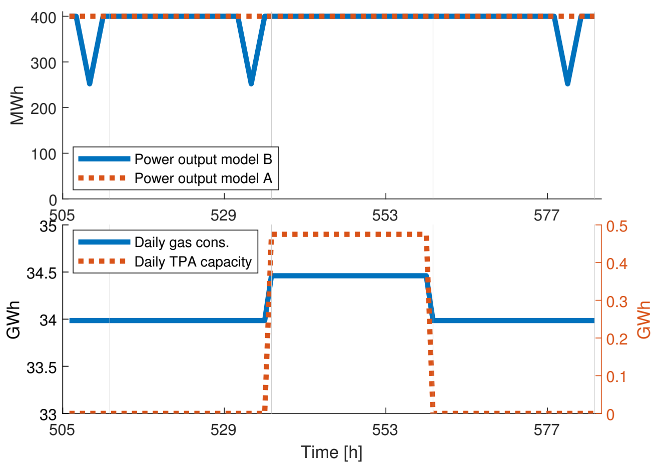

Fig. 10. Unit 6 power output in models A and Bfix (top), and gas consumption and daily TPA capacity in model Bfix (bottom). Results for scenario 9. Grey vertical lines indicate gas days.

GWh. With that capacity, the decision to produce power using more gas depends on the price of the daily capacity, which is more expensive than the monthly capacity. For that reason, with the electricity prices of gas days 21st and 23rd, model Bfix decides to produce some electricity but not the amount that would imply paying the extra cost for daily capacity. Finally, on day 22nd, electricity prices make it profitable enough to do the same as A, producing at full power output the whole day. The reason for these differences in behavior between models A and Bfix, is that A is not able to capture the actual cost reduction of lowering the power output to contract less or no daily capacity because it can not differentiate between daily and monthly capacities.

Regarding the combination of daily and monthly TPA capacities contracted, Fig. 11 shows the daily TPA capacity contracted for each scenario in October and Table III shows the monthly alternative. With respect to the monthly capacity, the simulation period starts in the middle of September and therefore no monthly contracting is possible for that month; in October, due to the nonanticipativity constraint, the same capacity is contracted for all scenarios; in November the monthly capacity is not profitable as only two days are included. The days for which the model contracts daily capacity are those that make it profitable to pay extra for that capacity in order to produce more energy to sell in the electricity market, whereas the days that no extra capacity is contracted are those where the model decides that it is better to reduce the cost and sell less electricity.

TABLE III
MONTHLY TPA CONTRACTED IN OCTOBER.

Exit points	GWh_t
Generators 1 & 2	32.40
Generator 3	17.40
Generator 4	17.58
Generators 5 & 6	33.98

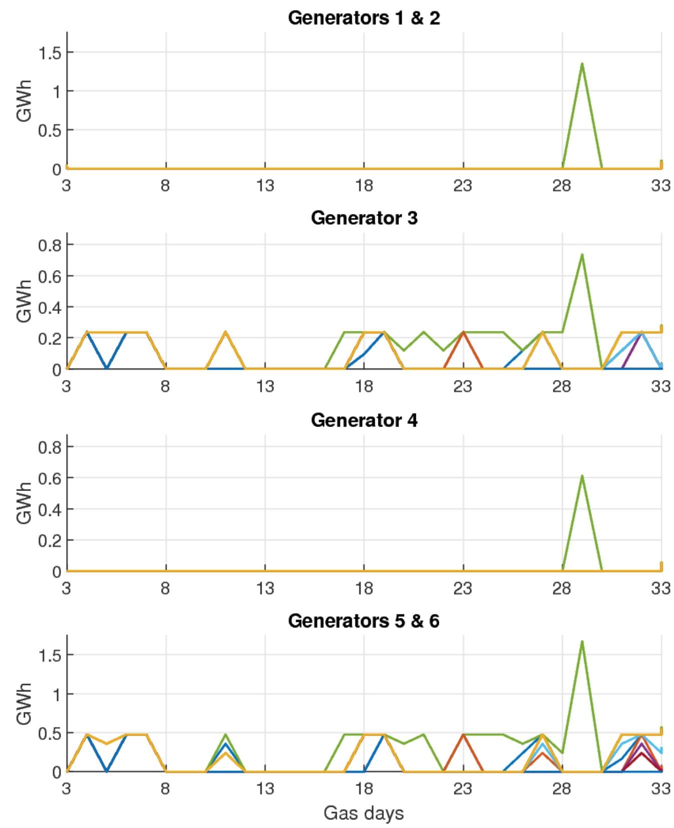

Fig. 11. Daily TPA capacity contracted for October at each exit point, for all scenarios.

C. Models B vs C

Models B and C consider the gas price elasticity in the market. Therefore, the more gas is purchased (sold) in the market, the more expensive (cheaper) the gas is. The data used for the first gas blocks available to buy each day are the same as in model Bfix, and the rest of the gas blocks have been multiplied by the factors displayed in Table VIII (appendix B).

Gas blocks quantity is fixed to 30GWh and a maximum of 270GWh is available to buy/sell each day.

The comparison between models B and C is focused on the interaction of markets. Table IV presents the main global results and Fig. 12 shows graphical results for one of the scenarios.

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TABLE IV
GLOBAL RESULTS FOR MODELS B AND C. EXPECTED VALUES (EV) AND STANDARD DEVIATIONS (σ).

	B		C	
	EV	σ	EV	σ
Electricity spot market				
Income [M€]	88.00	16.20	87.68	19.01
Gas used [GWh]	2279.97	424.25	2271.05	496.92
Electr. gen. [GWh]	1264.59	233.64	1259.76	273.29
Gas spot market				
Purchases [M€]	65.02	10.64	66.97	8.81
Income [M€]	0.00	0.00	2.38	4.98
Purchased gas [GWh]	2279.97	424.25	2343.92	369.00
Sold gas [GWh]	0.00	0.00	72.87	147.92
Regulated costs				
Storage cost [M€]	0.24	0.05	0.29	0.16
TPA cost [M€]	6.69	0.83	6.68	0.91
Global results				
Total costs [M€]	83.98	13.50	85.93	12.06
Total profits [M€]	4.02	3.20	4.13	3.10

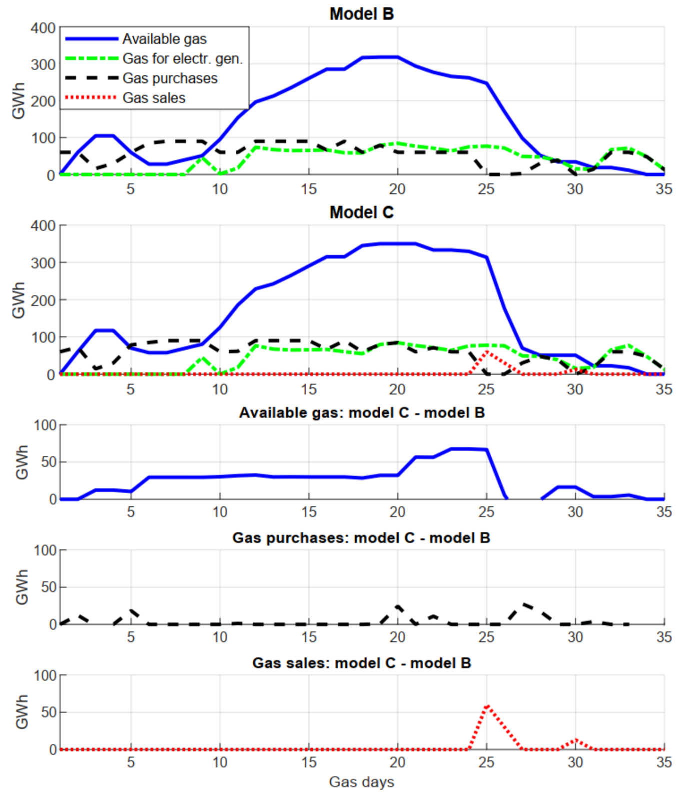

Fig. 12. Gas storage, purchases, sales, usage for electricity generation, and their differences for models B and C for in scenario 4.

From the results presented in Table IV it can be calculated that the gas available for electricity generation in model B has a price of 28.52€/MWh. Model C has a higher gas cost from purchases because buying larger quantities implies buying at higher prices. However, after subtracting the income from gas sales from the total gas cost, the gas available for electricity generation has a price of 28.44 €/MWh. As a result, model C has cheaper gas for electricity generation than model B.

With respect to the management of the gas storage, a different profile is obtained for each scenario. Fig. 12 shows the evolution of the available gas in the storage, the gas used for electricity generation, the gas purchases, the gas sales, and their differences for the particular case of scenario 4. It can be seen that the amount of gas used for electricity generation is very similar in both cases. Differences are higher when focusing on purchases and storage of gas as model C prefers to buy more gas than model B with the sole purpose of selling it when gas prices are higher. Model C sells 5.02% of the gas it buys.

VI. CONCLUSIONS

CCGTs will play an important role in the energy transition. This paper highlights the importance of representing in an accurate manner the costs incurred by the generation company that operates several CCGTs as they are subject to locational regulated TPA tariffs, regulated tariffs for storage usage, and must coordinate the total gas purchases in the gas spot market. The first conclusion of this paper is that neglecting all these issues can lead to inaccurate results, and therefore, standard UC and self-UC formulations need to be adapted when this kind of gas regulation is in force. A stochastic approach, considering electricity and gas prices uncertainty, has been applied to show that the common practice of neglecting TPA tariffs, can lead to wrong decisions. The second main conclusion is that the monthly TPA couples the operation of a whole month, and this can increase the complexity of the resulting problem. Finally, the example case has shown the applicability of the formulation to a realistic case, and besides the optimal hourly scheduling of the generators, the model can be used to help the company to decide the optimal values of monthly and daily capacity TPAs, and also to take advantage of storage services available in the infrastructure to increase their profits. This work could be extended to 1) study whether the current gas regulation of TPA could lead to an inefficient management of power plants and 2) to suggest regulatory changes in the affirmative case.

APPENDIX A
SELF-UC FORMULATION

This appendix includes all the equations of the stochastic self-UC model that are not related to the operational costs assessment presented previously in section III. These equations are inspired by the deterministic version of [48] and adapted to consider different scenarios. All the time periods are considered hourly periods for clarity.

Units are forced to stop at minimum power output.

$$p_{g,t,\omega} \leq (\overline{P_g} - \underline{P_g}) \cdot (v_{g,t,\omega} - z_{g,t+1,\omega}) \quad (31)$$

Units are forced to start at minimum power output.

$$p_{g,t,\omega} \leq (\overline{P_g} - \underline{P_g}) \cdot (v_{g,t,\omega} - y_{g,t,\omega}) \quad (32)$$

Total power output of the units.

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$$pt_{g,t,\omega} = \underline{P}_g \cdot v_{g,t,\omega} + p_{g,t,\omega} + \sum_{td \in TD_g} \left[PSD_{g,td} \cdot z_{g,t+1-td,\omega}\right] + \sum_{tu \in TU_g} \left[PSU_{g,tu} \cdot y_{g,t+TSU_g+1-tu,\omega}\right] \quad (33)$$

Constraint to ensure the coherence between commitment status, start-ups ad shut-downs.

$$\begin{array}{ll} y_{g,t,\omega} - v_{g,t,\omega} - z_{g,t,\omega} + IS_g = 0 & t = 1 \\ y_{g,t,\omega} - v_{g,t,\omega} - z_{g,t,\omega} + v_{g,t-1,\omega} = 0 & \forall t > 1 \end{array} \quad (34)$$

Minimum time on of the units.

$$\sum_{tt=t-TmnOn_g+1}^{t} \left[y_{g,tt,\omega}\right] = v_{g,t,\omega} \quad (35)$$

Minimum time off of the units.

$$\sum_{tt=t-TmnOff_g+1}^{t} \left[z_{g,tt,\omega}\right] = 1 - v_{g,t,\omega} \quad (36)$$

Maximum decrease in unit power output.

$$p_{g,t-1,\omega} - p_{g,t,\omega} \leq RD_g \quad (37)$$

Maximum increase in unit power output.

$$p_{g,t,\omega} - p_{g,t-1,\omega} \leq RU_g \quad (38)$$

Start-ups of the units limited to one each day.

$$\sum_{t \in \Omega_d^t} y_{g,t,\omega} \leq 1 \; \forall d \in D \quad (39)$$

Relation between type of start-up and number of hours that the unit has been off.

$$\delta_{g,t,su,\omega} \leq \sum_{tt=1+TmnS_{g,su}}^{TmnS_{g,su+1}} \left[z_{g,t-tt+1,\omega}\right] \quad \begin{array}{ll} \forall t & \in [TmnS_{g,su+1} - TDo_g, T] \\ \forall su & \in [1, SU) \end{array} \quad (40)$$

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

$$\sum_{su \in SU} \left[\delta_{g,t,su,\omega}\right] = y_{g,t,\omega} \quad (41)$$

Appendix B
Case Study Data

This appendix presents the main data for the case study. Generators characteristic, gas and electricity prices for the 210 generated scenarios, the reduced scenario trees, and the real data are available online in [57]. The process to calculate the values of the cost parameters used to model the cost of the units in model A is detailed in Algorithm 1.

Algorithm 1 Pseudocode to compute the cost parameters for model A

- Run the model Bfix.
- From the obtained results, compute the hourly cost of each generation unit: Emissions cost + O&M cost + TPA cost + Gas storage cost + Supply cost. TPA, gas storage, and supply costs are assigned to each hour and generation unit proportionally to their hourly consumption.
- For each generation unit, compute the linear regression of the obtained points (power output, hourly cost), taking into account the scenario probabilities.
- Parameter $CSvr_g$ is determined as the slope of the linear equation, and $CSmn_g$ is the value that corresponds to the minimum stable load $\underline{P}_g$.
- Parameters $CSsd_{g,su}$ and $CSsu_{g,su}$ are estimated as the weighted average values of the hourly cost incurred by the generation units when shutting down and starting-up, respectively.

TABLE V
GENERATORS' CHARACTERISTICS.

	Group1	Group2	Group3	Group4	Group5	Group6
Pmx [MW]	385.00	390.00	400.00	405.00	390.00	400.00
Pmn [MW]	128.33	195.00	200.00	135.00	195.00	200.00
RU [MW/h]	55.00	70.00	74.00	76.00	70.00	74.00
RD [MW/h]	55.00	70.00	74.00	76.00	70.00	74.00
TmnOn [h]	2	2	2	2	2	2
TmnOff [h]	2	3	3	2	3	3
RSU [MW/h]	82.50	77.00	81.40	114.00	77.00	81.40
RSD [MW/h]	128.33	195.00	200.00	135.00	195.00	200.00
ComIni [MW]	50.00	50.00	50.00	50.00	50.00	50.00
TmnSUh [h]	0	0	0	0	0	0
TmnSUw [h]	12	12	12	12	12	12
TmnSUc [h]	24	24	24	24	24	24
CSmn [k€/h]	7.989	11.975	12.457	9.312	11.975	12.457
CSvr [€/MWh]	43.21	43.88	45.19	44.86	43.88	45.19
CSsuH [k€]	16.035	17.106	17.107	19.231	17.107	17.107
CSsuW [k€]	22.330	23.660	23.660	26.360	23.660	23.660
CSsuC [k€]	28.624	30.212	30.212	33.489	30.212	30.212
CSsd [k€]	1.916	1.835	1.835	1.846	1.835	1.835
CNmn [MWh_t/h]	255.16	396.93	414.03	302.32	396.93	414.03
CNvr [MWh_t/MWh]	1.54	1.56	1.60	1.59	1.56	1.60
CNsuH [MWh_t]	436.13	465.20	465.20	523.35	465.20	465.20
CNsuW [MWh_t]	654.19	697.80	697.80	785.03	697.80	697.80
CNsuC [MWh_t]	872.25	930.41	930.41	1046.71	930.41	930.41
CNsd [MWh_t]	65.13	65.13	65.13	65.13	65.13	65.13
OMh [€/h]	800	800	800	800	800	800
OMsu [€]	4000	4000	4000	4000	4000	4000
CO2r[t/GWh_t]	202	203	205	206	211	212

TABLE VI
THIRD PARTY ACCESS DATA.

$Tu_{x,m}$ [€/MWh_t]	$Td_{x,m}$ [€/MWh_t]	$Tm_{x,m}$ [€/MWh_t]	$Tp_{x,m}$ [MWh_t]
0.847	3.110	44.928	0.000

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TABLE VII
STORAGE DATA.

$Sd_{x,m}$ [€/MWh$_t$]	$Sm_{x,m}$ [€/MWh$_t$]	$Sp_{x,d}$ [MWh$_t$]	Si_x [€/MWh$_t$]	Se_x [€/MWh$_t$]
0.037	0.534	0.000	0.244	0.131

TABLE VIII
GAS PRICE FACTORS FOR EACH GAS BLOCK.

Blocks	Purchases	Sales
1	1.0000	0.9925
2	1.0075	0.9703
3	1.0303	0.9345
4	1.0696	0.8865
5	1.1270	0.8284
6	1.2054	0.7626
7	1.3086	0.6915
8	1.4421	0.6177
9	1.6132	0.5435
10	1.8317	0.4710

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