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Optimal self-unit commitment of combined cycle power plants. Bridging the gap between the state of the art and current regulation of electricity and natural gas markets.

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A mis padres.

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Summary

Gas Fired Units (GFUs), especially Combined Cycle Gas Turbines (CCGTs), will play an essential role in the transition to the decarbonization of the power industry. One of the fundamental problems faced by a Generation Company (GenCo) with GFUs is known as the Unit Commitment (UC) problem, and as it affects its own generation, this problem is also known in the literature as self Unit Commitment (self-UC). The UC is one of the most studied problems in the power systems literature, consisting in deciding the commitment status of the generation units. The UC is critical because the units take a minimum time to start up and shut down so that the commitment state in a given hour is linked to the surrounding periods, whereas with a unit already connected, varying the load level from one hour to another is more flexible. In particular, the correct modeling of GFUs is vital in deregulated market environments organized as marginal markets since, in most situations, this type of units is decisive for the resulting market cleared price.

The GFUs have an added complexity not applicable to other thermal units such as coal or nuclear, that is receiving their fuel supply through a gas network. This gas network is in some ways analogous to the electricity network, but it has its own characteristics that need to be considered for the GFUs operation. The gas network has a Transmission System Operator (TSO) in charge of its operation. This operation entails associated costs that the TSO passes on to the gas network users through the so-called Third Party Access (TPA) tariffs. From the point of view of a GenCo that owns GFUs and participates in the electricity market, two fundamental issues must be considered concerning the fuel supply for its units: the TPA tariffs that must be paid to extract gas from the network at the power plants where the GFUs are located, and the available options to acquire the gas. Regarding gas procurement, there are mainly two options, bilateral contracts with suppliers and purchases in gas spot markets. Irrespective of whether the company has bilateral agreements with suppliers, if it operates in an area with a sufficiently liquid gas spot market, the price of that market will be its supply cost. On the one hand, if the GenCo buys on the gas spot market directly, that price is the cost for the GFUs. On the other hand, if it has bilateral contracts, the market price becomes the opportunity cost of using the gas already acquired for electricity generation as an alternative to selling that gas to the spot market.

Another aspect to consider that is usually simplified is the tax scheme to which the generation units are subject. Taxes are part of the generation units operating costs. A careful review of current taxation systems shows different tax types. For instance, taxes

charge concepts such as the energy generation [€/MWh], the market revenue [market price percentage] or greenhouse gas emissions [€/ton]. Additionally, these taxes can differ depending on the technology used to generate electricity (coal, gas, hydro, nuclear, etc.), and even they can depend on geographical areas belonging to the same market. These possible differences make it essential to model them in detail to take them into account correctly.

Finally, as in any other market, agents are expected to try to maximize their expected profits. In an environment with perfect competition, this situation requires no additional consideration. However, when the number of GenCos is reduced, there are specific regulations aiming to limit possible strategic behaviors of dominant players. In the case of the power sector, those rules have widely been implemented; therefore, agents participating in the electricity market need to account for such regulation in their own planning.

Considering the vital role that GFUs will continue to play in the future, the need to solve the lack of state-of-the-art models to address issues that significantly affect the real operation of these units in the market becomes essential. Therefore, this thesis begins by explaining in detail the problems briefly presented in this summary, starting with a detailed review of how the gas system works, focusing on TPA tariffs in the European Union. In addition, it also reviews the different taxes applied to the electricity generation activity and how these problems are tackled in the optimization modeling literature.

These issues were not found in the literature on the short-term self-UC optimization models, which are the tools GenCos use in their day-to-day operation planning. Additionally, the relevance of the TPA consideration, that accounts for more than 10% of the total operation cost, has been confirmed by our own experience in collaborations with the industry. Therefore, several modeling improvements have been developed and are proposed in this document. The different chapters present several models with their respective case studies to demonstrate their usefulness in the subjects they address. They are not specific models for each one of the issues but instead represent the different improvements that would have to be implemented to cover each of the concepts discussed, and they could, in fact, be integrated. Chapter 3 proposes modeling TPA tariffs and gas purchases at the portfolio level. Chapter 4 offers a model that represents the individual revenues of each unit to correctly consider its taxes and the possibility that different agents share the ownership of generation assets. Lastly, Chapter 5 presents two different approaches to limit the strategic behaviors that could result from applying the models found in the literature.

The thesis's objective is general, and therefore, the developments presented are not only valid for a GenCo operating CCGTs in a specific country. The improvements in the representation of gas are based on European regulation (whose objective is similar to that of other countries), and those related to income modeling are extensible to other generation technologies. In fact, the correct tax representation gains importance when the portfolio has several technologies subject to different levies. Finally, regarding the potential users of the proposed models, it is clear that GenCos find a direct application in planning their own operation. In addition, they are also helpful tools for regulators or System Operator (SO), providing them with the means to simulate and study the expected behavior of the agents participating in the market.

Finally, three appendices are presented with the objective of providing all the necessary tools to optimize the self-UC with GFUs. The first appendix is dedicated to the UC modeling and how to take uncertainty into account by using stochastic programming. The second appendix presents the formulation changes that should be implemented in case of having CCGTs with multiple configurations of gas and steam turbines. Such consideration is thought to be valuable since this type of unit is very common in the industry. Finally, the third appendix presents an example of how to run a self-UC optimization model in a cloud computing environment, a standard that is gaining traction in the industry.

Resumen

Los grupos térmicos generadores que utilizan gas natural como combustible (Gas Fired Units (GFUs)), especialmente los ciclos combinados (Combined Cycle Gas Turbines (CCGTs)), desempeñarán un papel esencial en la transición hacia la descarbonización del sector eléctrico. Uno de los problemas fundamentales a los que se enfrenta una compañía generadora (Generation Company (GenCo)) propietaria de un conjunto de GFUs es el problema denominado “unit commitment” (Unit Commitment (UC)). Al restringirse a los grupos propiedad de la empresa a este problema se le conoce como self Unit Commitment (self-UC). El UC es uno de los problemas más estudiados en la literatura de sistemas eléctricos y consiste en decidir el estado de acoplamiento de los grupos generadores en cada hora del horizonte temporal considerado. El UC es especialmente crítico porque los grupos tardan un tiempo mínimo en arrancar y parar, por lo que el acoplamiento de una hora determinada está condicionado por el de las horas adyacentes, mientras que una vez encendido la variación del nivel de carga entre horas es más flexible. Concretamente, modelar de manera correcta los grupos GFUs es de vital importancia en mercados marginalistas, ya que, en gran parte de las situaciones, este tipo de unidades son decisivas para la determinación del precio de casación.

Los grupos GFUs tienen una complejidad añadida respecto a otras unidades térmicas tradicionales como el carbón o la nuclear, que es la de recibir el combustible a través de una red de transporte (gasoductos). Esta red de gas es, en cierto modo, análoga a la red eléctrica, pero tiene unas características propias que es importante tener en cuenta. La red de gas está gestionada por un operador (Transmission System Operator (TSO)) encargado de su operación. Esta operación conlleva unos costes asociados que el TSO traslada a los usuarios de la red de gas a través de las tarifas denominadas de acceso de terceros (Third Party Access (TPA)). Desde el punto de vista de una GenCo propietaria de GFUs y que participa en el mercado eléctrico, hay que considerar dos cuestiones fundamentales en relación con el suministro de combustible para sus generadores: las tarifas TPA que debe pagar para extraer el gas de la red en las centrales donde se ubican los GFUs, y las opciones disponibles para adquirir dicho gas. En cuanto a la adquisición de gas, existen principalmente dos opciones: contratos bilaterales con proveedores y compras en mercados spot. Independientemente de que la empresa tenga acuerdos bilaterales de suministro con proveedores, si opera en una zona que tenga un mercado spot de gas suficientemente líquido, el precio de ese mercado será el coste de su gas ya que, si la GenCo compra en el mercado spot de gas directamente, ese precio es el coste para los GFUs. Por otro lado, si tiene contratos bilaterales, el precio de mercado se convierte en el coste de oportunidad de utilizar el gas adquirido en esos contratos para

generar electricidad como alternativa a venderlo en el mercado spot de gas.

Otro aspecto a considerar, y que suele simplificarse, es el régimen impositivo al que están sometidos los generadores. Los impuestos son parte de los costes de explotación de los grupos. Analizando con detalle los sistemas fiscales actuales observamos que existen distintos tipos de impuestos. Por ejemplo, los impuestos gravan conceptos como la generación de energía [€/MWh], los ingresos del mercado [porcentaje del precio del mercado] o las emisiones de gases de efecto invernadero [€/tonelada]. Además, estos impuestos pueden ser distintos en función de la tecnología (carbón, gas, hidroeléctrica, nuclear, etc.), e incluso depender de las zonas geográficas pertenecientes a un mismo mercado. Estas posibles diferencias entre grupos generadores hacen que sea importante modelar los impuestos con detalle para evaluar con mayor precisión el gasto de explotación real asociado a una determinada programación horaria de los generadores.

Por último, como en cualquier otro mercado, se espera que los agentes traten de maximizar sus beneficios esperados. En un entorno de competencia perfecta, esta situación no requiere ninguna consideración adicional. Sin embargo, cuando el número de GenCos es reducido, existen normas específicas destinadas a limitar posibles comportamientos estratégicos de agentes dominantes. En el caso del sector eléctrico, estas normas se han implantado de forma generalizada en muchos sistemas, por lo que los agentes que participan en el mercado eléctrico deben tener en cuenta dicha regulación en su planificación.

Considerando la relevancia que tienen y seguirán teniendo los GFUs en el sistema eléctrico, surge la necesidad de resolver las carencias existentes en los modelos del estado del arte para dar respuesta a cuestiones que afectan significativamente a la operación real de estos generadores en el mercado. Por tanto, esta tesis comienza explicando en detalle los problemas presentados brevemente en este resumen, empezando por una revisión detallada del funcionamiento del sistema gasista, centrándose en las tarifas TPA en la Unión Europea. Además, también se revisan los diferentes impuestos aplicados a la actividad de generación eléctrica y cómo se abordan estos problemas en la literatura de modelos de optimización.

Como se ha mencionado anteriormente, en la revisión del estado del arte no se ha encontrado que estos temas se traten en los modelos de optimización de self-UC de corto plazo, que son precisamente las herramientas que utilizan las GenCos para planificar su operativa diaria. Además, la pertinencia de considerar las tarifas de TPA, que representan más del 10% del coste total de operación de los GFUs, ha sido confirmada durante la realización de esta investigación a través de proyectos desarrollados en estrecha colaboración con la industria. Por lo tanto, se han desarrollado varias mejoras de modelado para tratar de afrontar dichos problemas. En los siguientes capítulos se presentan varios modelos abordando cada uno de los aspectos identificados, acompañados de sus respectivos ejemplos con los que demostrar su utilidad. No se trata de modelos aislados específicos para cada una de las cuestiones, sino que en cada capítulo se presentan las ecuaciones y propuestas para cubrir el concepto que se trata, pero posteriormente podrían integrarse en un solo modelo. El capítulo 3 propone el modelado de las tarifas de TPA y las compras de gas a nivel de portfolio. El capítulo 4 ofrece un modelo que representa los ingresos individuales de cada generador para poder considerar correctamente sus impuestos y la propiedad compartida de los activos de generación. Por último, el capítulo 5 presenta dos enfoques diferentes para limitar los posibles comportamientos estratégicos que derivan de una aplicación directa de los modelos encontrados en la literatura.

El objetivo de la tesis tiene un carácter general, y por tanto los desarrollos presentados no son solo útiles para una GenCo que opera CCGTs en un país especifico. Las mejoras de la representación del gas se basan en la regulación de ámbito europeo (cuyo objetivo es similar al de otros países), y aquellas relacionadas con el modelado de los ingresos son extensibles a otras tecnologías de generación. De hecho, la correcta representación de los impuestos gana importancia cuando existen diversas tecnologías en el portfolio sujetas a tasas distintas. Por último, respecto a los potenciales usuarios de los modelos propuestos, está claro que para las GenCos tienen una aplicación directa en la planificación de su propia operación. Adicionalmente, también son herramientas de gran utilidad para reguladores u operadores del sistema, proporcionándoles medios con los que simular y estudiar los comportamientos esperados de los agentes que participan en el mercado.

Finalmente, se presentan tres apéndices con el objetivo de proporcionar todas las herramientas necesarias para optimizar el self-UC con GFUs. El primer apéndice está dedicado al modelado del UC en sí, y a cómo tener en cuenta la incertidumbre usando técnicas de optimización estocástica. El segundo apéndice presenta los cambios que habría que implementar en la formulación en caso de tener CCGTs con múltiples configuraciones de turbinas de gas y vapor. Esta consideración se entiende valiosa ya que es un tipo de generador bastante común en la industria. Finalmente, el proceso de digitalización en el que se hayan actualmente inmersas la mayoría de empresas que operan en distintos sectores industriales también se está implantando en las empresas generadoras de electricidad. Por ello, el tercer apéndice de esta tesis presenta un ejemplo de cómo ejecutar un modelo de optimización de self-UC en un entorno de computación en la nube.

Ukrainian War 2022

On February 24, 2022, when Vladimir Putin announced a "special military operation" aimed at "demilitarizing and denazifying" Ukraine, Russia launched an invasion of Ukraine in a significant escalation of the Russian-Ukrainian conflict. The attack triggered a major refugee crisis in Europe. Around a third of the population was displaced, and almost 8 millions left the country. This invasion has received widespread international condemnation, and many countries have imposed sanctions on Russia. With Ukraine being one of the world's larger agricultural producers and Russia a major raw material exporter, the development of the war on Ukrainian soil and the rapid deterioration of Russia's international relations are leading to global food shortages and soaring prices for energy products such as oil and gas.

This thesis primarily focuses on gas-fired power generation units, and most of its developments predate this conflict. Therefore, some situations and study cases presented throughout this document may differ from the current situation in international markets. The impact of this war on the future availability and prices of natural gas remain unknown at the moment of the dissertation.

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Acronyms

AWS Amazon Web Services. xxi, 29, 30, 169–172, 175–186

CCGT Combined Cycle Gas Turbine. iii–v, vii, ix, 12, 15, 17, 23, 27–30, 36, 38, 39, 42, 52, 55, 56, 59–61, 63, 64, 72, 82, 144, 149, 161, 169

CCPP Combined Cycle Power Plant. 41

CVaR Conditional Value at Risk. 61, 62

ECR Elastic Container Registry. 170–172, 175, 182

ECS Elastic Container Service. 172, 179, 185

EU European Union. 11, 18, 19, 21, 26, 56

EV Expected Value. 77, 81

FERC Federal Energy Regulatory Commission. 42

GAMS General Algebraic Modeling Language. 54, 170, 173, 182

GDP Gross Domestic Product. 11

GenCo Generation Company. iii, iv, vii–ix, 12–15, 17, 19, 21, 24, 25, 28, 30, 34, 36, 41, 43–47, 49, 55, 56, 60–64, 68, 71, 82, 85, 86, 88, 107–111, 114, 115, 125–129, 131, 134, 135, 139, 142–146, 148

GFU Gas Fired Unit. iii–v, vii–ix, 12, 13, 19, 39, 42, 59, 141–143, 145, 148

GRU Gated Recurrent Units. 72, 74

GT Gas Turbine. xxi, 159–162

HRSG Heat Recovery Steam Generator. xxi, 41, 159, 160, 162

IAM Identity and Access Management. 178

IEA International Energy Agency. 12, 14

IEEE Institute of Electrical and Electronics Engineers. 59, 85, 147

IIT Institute for Research in Technology. 144

IMING Internal Market In Natural Gas. 18, 19

IVPEE Impuesto sobre el Valor de la Producción de la Energía Eléctrica. 26

LNG Liquefied natural gas. 14, 17, 19

LSTM Long Short-Term Memory. 72

LTSA Long-Term Service Agreements. 42

MILP Mixed Integer Linear Programming. 41, 44, 46, 51, 52, 56, 63

MISO Midcontinent Independent System Operator. 34

MPEC Mathematical Programming with Equilibrium Constraints. 44

O&M Operation and Maintenance. 6, 52, 65, 66, 90, 92, 129

OS Operating System. 170, 181

P2G Power-to-Gas. 12

PBUC Profit Based Unit Commitment. 34

PDE Partial Differential Equation. 35–37

RES Renewable Energy Sources. 12, 39

S3 Simple Storage Service. xxvii, 170–172, 177

SCUC Security-Constrained Unit Commitment. 39

self-UC self Unit Commitment. iii–v, vii–ix, 28, 30, 33, 34, 43, 44, 55, 56, 60–62, 64, 70, 82, 86, 93, 144, 146, 149, 155

SO System Operator. iv, 16, 17, 19, 21, 33, 34, 40, 55

ST Steam Turbine. xxi, 159–162

TPA Third Party Access. iii, iv, vii, viii, xix, xx, xxv, 6, 7, 13, 18, 19, 21, 23, 28, 29, 40, 41, 52, 56, 59–66, 70–72, 76–83, 142–148

TSO Transmission System Operator. iii, vii, 18, 19, 21, 72

UC Unit Commitment. iii, v, vii, ix, 13, 14, 33, 34, 36, 41, 42, 51, 53, 55, 61, 63, 64, 82, 86, 108, 130, 136–139, 141, 149, 162

UK United Kingdom. 18, 21

USA United States of America. 18, 21, 42, 108

UTC Universal Coordinated Time. 21

VPC Virtual private Network. 180

Nomenclature

In the academic world, it is usually an unwritten rule to use the shortest possible names for sets, parameters and variables so that equations can be written more compactly in terms of the space they occupy in the text. On the contrary, in the programming world –where the limitations on the number of characters per line and the number of lines are practically non-existent–, it is considered a good practice to use sufficiently descriptive names. Readability is valued above anything else, and more concise and generally cryptic code is deemed poor quality. This thesis is in A4 format, so its horizontal space is limited. Therefore, very long equations would require too many lines to be written, which would also be counterproductive. For that reason, a middle ground has been chosen, trying to have short names but descriptive enough that make it easier for the reader to follow the formulation.

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 w indicates the dependence on a scenario for variables, parameters and subsets when modeling stochasticity and should be omitted for the deterministic version. Superscripts s' and s'' are used as aliases for sets.

Domain definitions:

- Reals: $\mathbb{R}$
- Non-negative reals: $\mathbb{R}^+ = \{x : x \geq 0, x \in \mathbb{R}\}$
- Per unit: $\mathbb{P} = \{x : 0 \leq x \leq 1, x \in \mathbb{R}\}$
- Binary: $\mathbb{B} = \{0, 1\}$
- Integers: $\mathbb{Z}$
- Non-negative integers: $\mathbb{Z}^+ = \{x : x \geq 0, x \in \mathbb{Z}\}$

Sets

$g, g' \in G$	Generator units {G1 to G}.
$G^{ind} \subset G$	Subset of generators to which enforcing commitment constraints based on individual income are applied.
$t, t', t'' \in T$	Hourly time periods {1 to T}.

$d \in D$	Days {1 to D}.
$m \in M$	Months {1 to M}.
$dg \in DG$	Gas days {1 to DG}.
$mg \in MG$	Gas months {1 to MG}.
Ω_d^t	Hours t belonging to day d.
Ω_t^d	Day d to which hour t belongs.
Ω_{dg}^t	Hours t belonging to gas day dg.
Ω_t^{dg}	Gas day dg to which hour t belongs.
Ω_{mg}^{dg}	Gas days dg belonging to gas month mg.
Ω_{dg}^{mg}	Gas month mg to which gas day dg belongs.
$su \in SU$	Start-up type {1 (hottest) to SU (coldest)}.
$tu \in TU$	Hourly time periods of the start-up trajectories {1 to TU}.
$td \in TD$	Hourly time periods of the shut-down trajectories {1 to TD}.
$tr \in TR$	Time steps of the reference generation profile.
Ω_g^{tu}	Existing time periods of the start-up trajectory tu for each generation unit g.
Ω_g^{td}	Existing time periods of the shut-down trajectory td for each generation unit g.
$s \in S$	Income curve segments {1 to S}.
$c \in C$	Income curve concave intervals {1 to C}.
$\Omega_{w,t}^s$	Existing segments s in each hour t for each scenario w.
$\Omega_{w,t}^c$	Existing concave intervals c in each hour t for each scenario w.
$\Omega_{w,t}^{cs}$	Existing combinations of segments s and concave interval c in each hour t for each scenario w.
$i \in I$	Residual demand curve segments {1 to I}.
$\Omega_{w,t}^i$	Existing segments i in each hour t for each scenario w.
$x \in X$	Exit points of the gas network {1 to X}.
$b \in B$	Gas blocks {1 to B}.
$w, w', w'' \in W$	Scenarios {1 to W}.
$\Omega_{w,t}^{w'}$	Scenario w' that represents scenario w at period t.
$\Omega_{w,d}^{w'}$	Scenario w' that represents scenario w at period d.

$\Omega_{w,dg}^{w'}$	Scenario w' that represents scenario w at period dg.
$\Omega_{w,mg}^{w'}$	Scenario w' that represents scenario w at period mg.
Ω_{t}^{w}	Representative scenarios w at period t.
Ω_{d}^{w}	Representative scenarios w at period d.
Ω_{dg}^{w}	Representative scenarios w at period dg.
Ω_{mg}^{w}	Representative scenarios w at period mg.

Variables

$incT_{w,t} \in \mathbb{R}$	Total income at hour t [€].
$qI_{w,s,t} \in \mathbb{R}^{+}$	Power in segment s of the income curve at hour t [MWh].
$qbinI_{w,c,t} \in \mathbb{B}$	Activation variable of income curve concave intervals c at hour t.
$incG_{w,g,t} \in \mathbb{R}^{+}$	Income for generator g at hour t [€].
$a_{w,i,t} \in \mathbb{B}$	Activation variable of residual demand curve segment i at hour t.
$a_{w,g,i,t,tr}^{g} \in \mathbb{B}$	Activation variable of residual demand curve segment i at hour t, to analyze the commitment of g during the reference profile of tr.
$apt_{w,i,g,t} \in \mathbb{R}^{+}$	$pt_{g,t}$ when $a_{i,t}$ is active, 0 otherwise [MWh].
$p_{w,g,t} \in \mathbb{R}^{+}$	Power generated over $\underline{P}_g$ by generator g at hour t [MWh].
$pt_{w,g,t} \in \mathbb{R}^{+}$	Total power generated by generator g at hour t [MWh].
$csG_{w,g,t} \in \mathbb{R}^{+}$	Cost of generator g [€].
$v_{w,g,t} \in \mathbb{B}$	Commitment status of generator g at hour t.
$y_{w,g,t} \in \mathbb{B}$	Start-up decision of generator g at hour t.
$z_{w,g,t} \in \mathbb{B}$	Shut-down decision of generator g at hour t.
$\delta_{w,g,su,t} \in \mathbb{B}$	Start-up decision of generator g at hour t for start-up type su.
$cnG_{w,g,t} \in \mathbb{R}^{+}$	Fuel consumption of generator g at hour t [$\mathrm{MWh_t}$]
$csCN_{w,g,t} \in \mathbb{R}$	Fuel cost of generator g at hour t [€]
$csCO2_{w,g,t} \in \mathbb{R}^{+}$	CO_2 emission cost of generator g at hour t [€]
$csTot_{w} \in \mathbb{R}$	Total cost of the generators [€].
$cnX_{w,x,dg} \in \mathbb{R}^{+}$	Gas consumption at exit point x on gas day dg [$\mathrm{MWh_t}$].

$dT_{w,x,dg} \in \mathbb{R}^+$	Daily TPA capacity at exit point x on gas day dg [MWh_t].
$mT_{w,x,mg} \in \mathbb{R}^+$	Monthly TPA capacity at exit point x on gas month mg [MWh_t].
$qa_{w,dg,} \in \mathbb{R}^+$	Daily available gas on gas day dg [MWh_t].
$qb_{w,dg,} \in \mathbb{R}^+$	Gas purchases on gas day dg [MWh_t].
$qb_{w,dg,b} \in \mathbb{R}^+$	Gas purchases on gas day dg per block b [MWh_t].
$qs_{w,dg,b} \in \mathbb{R}^+$	Gas sales on gas day dg per block b [MWh_t].
$dS_{w,x,mg} \in \mathbb{R}^+$	Daily storage capacity at point x on gas month mg [MWh_t].
$mS_{w,x,mg} \in \mathbb{R}^+$	Monthly storage capacity at point x on gas month mg [MWh_t].
$iS_{w,x,dg} \in \mathbb{R}^+$	Gas injection to storage facility at point x on gas day dg [MWh_t].
$eS_{w,x,dg} \in \mathbb{R}^+$	Gas extraction from storage facility at point x on gas day dg [MWh_t].
$csT_{w,x,mg} \in \mathbb{R}^+$	TPA cost at point x on gas month mg [€].
$csSup_{w,dg} \in \mathbb{R}$	Gas supply cost on gas day dg [€].
$csS_{w,x,mg} \in \mathbb{R}^+$	Gas storage cost at point x on gas month mg [€].
$csOM_{w,g,t} \in \mathbb{R}^+$	Operation and Maintenance (O&M) cost of unit g at hour t [€].
$incTh_{w,g,t} \in \mathbb{R}^+$	Theoretical revenue of g using the reference generation profile if committed at period t [€].
$incThMax_{w,g} \in \mathbb{R}^+$	Maximum value of $incTh_{w,g,t}$ during the day [€].
$incThMaxB_{w,g,t} \in \mathbb{B}$	Auxiliary binary variable used to ensure that $incThMax_{w,g}$ is the maximum value of $incTh_{w,g,t}$.
$incThMaxBh_{w,g,t} \in \mathbb{B}$	Time periods where g has to be committed with the reference generation profile to obtain the maximum theoretical revenue.
$forceOn_{w,g} \in \mathbb{B}$	Binary variable to enforce the commitment of g if the potential revenue is higher than the corresponding cost.
$aRD_t \in \mathbb{R}^+$	Area under the residual demand curve at hour t [€].
$qRD_{i,t} \in \mathbb{R}^+$	Energy in each segment of the residual demand curve at hour t [MWh].
$txG_{w,g,t} \in \mathbb{R}^+$	Total tax expense of unit g at hour t [€].
$txE_{w,g,t} \in \mathbb{R}^+$	Generation tax expense per energy produced of unit g at hour t [€].
$txI_{w,g,t} \in \mathbb{R}^+$	Generation tax expense per income of unit g at hour t [€].
$txIaprox_{w,g,t} \in \mathbb{R}^+$	Approximation of the generation tax expense per income of unit g at hour t [€].
$txCN_{w,g,t} \in \mathbb{R}^+$	Fuel tax expense of unit g at hour t [€].
$txCO2_{w,g,t} \in \mathbb{R}^+$	CO_2 tax expense of unit g at hour t [€].

Parameters

$CSmn_g \in \mathbb{R}^+$	Generation cost at $\underline{P}_g$ of generator g [€/h].
$CSvr_g \in \mathbb{R}^+$	Variable cost of generator g [€/MWh].
$CSsu_{g,su} \in \mathbb{R}^+$	Start-up cost of generator g for start-up type su [€].
$CSsd_g \in \mathbb{R}^+$	Shut-down cost of generator g [€].
$Tp_{x,dg} \in \mathbb{R}^+$	Pre-contracted TPA capacity at exit point x on gas day dg [$\mathrm{MWh_t}$/day].
$Tu_{x,mg} \in \mathbb{R}^+$	Price of pipeline usage at exit point x on gas month mg [€/$\mathrm{MWh_t}$].
$Td_{x,mg} \in \mathbb{R}^+$	Daily capacity price at exit point x on gas month mg [€/$\mathrm{MWh_t}$/day].
$Tm_{x,mg} \in \mathbb{R}^+$	Monthly capacity price at exit point x on gas month mg [€/$\mathrm{MWh_t}$/day].
$\mathit{\Pi}^E_{w,t} \in \mathbb{R}^+$	Hourly electricity marginal price at hour t [€/MWh].
$\mathit{\Pi}^G_{w,dg} \in \mathbb{R}^+$	Daily gas marginal price on gas day dg [€/$\mathrm{MWh_t}$].
$OMh_g \in \mathbb{R}^+$	Operation and maintenance cost of generator g for each hour [€/h].
$OMsu_g \in \mathbb{R}^+$	Operation and maintenance cost of generator g for each start-up [€/su].
$Avail \in \mathbb{R}^+$	Initial available gas [$\mathrm{MWh_t}$].
$Sd_{x,dg} \in \mathbb{R}^+$	Daily storage capacity price at point x on gas day dg [€/$\mathrm{MWh_t}$/day].
$Sm_{x,mg} \in \mathbb{R}^+$	Monthly storage capacity price at point x on gas month mg [€/$\mathrm{MWh_t}$/day].
$Sp_{x,dg} \in \mathbb{R}^+$	Pre-contracted storage capacity at point x on gas day dg [$\mathrm{MWh_t}$/day].
$Si_x \in \mathbb{R}^+$	Injection cost to storage facility at point x [€/$\mathrm{MWh_t}$].
$Se_x \in \mathbb{R}^+$	Extraction cost from storage facility at point x [€/$\mathrm{MWh_t}$].
$BuyQ_{w,dg,b} \in \mathbb{R}^+$	Gas quantity to buy on gas day dg for block b [$\mathrm{MWh_t}$].
$SellQ_{w,dg,b} \in \mathbb{R}^+$	Gas quantity to sell on gas day dg for block b [$\mathrm{MWh_t}$].
$Buy\mathit{\Pi}^G_{w,dg,b} \in \mathbb{R}^+$	Gas market price to buy on gas day dg for block b [€/$\mathrm{MWh_t}$].
$Sell\mathit{\Pi}^G_{w,dg,b} \in \mathbb{R}^+$	Gas market price to sell on gas day dg for block b [€/$\mathrm{MWh_t}$].
$Prob_w \in \mathbb{P}$	Probability of scenario w [p.u.].
$\underline{I}_{w,t} \in \mathbb{R}^+$	Income for the minimum power of the income curve at hour t [€].
$\underline{Iq}_{w,s,t} \in \mathbb{R}^+$	Minimum power of income curve segment s at hour t [MWh].
$\overline{Iq}_{w,s,t} \in \mathbb{R}^+$	Maximum power of income curve segment s at hour t [MWh].

$Islp_{w,s,t} \in \mathbb{R}^+$	Slope of income curve segment s at hour t [€/MWh].
$RD\Pi^E_{w,i,t} \in \mathbb{R}^+$	Price of residual demand curve segment i at hour t [€/MWh].
$\underline{RDq}_{w,i,t} \in \mathbb{R}^+$	Minimum power of residual demand curve segment i at hour t [MWh].
$\overline{RDq}_{w,i,t} \in \mathbb{R}^+$	Maximum power of residual demand curve segment i at hour t [MWh].
$Own_g \in \mathbb{P}$	Percentage of ownership of generator g [p.u.].
$CNmn_g \in \mathbb{R}^+$	Consumption at $\underline{P}_g$ of generator g [$\mathrm{MWh_t}$/h].
$CNvr_g \in \mathbb{R}^+$	Variable consumption of generator g [$\mathrm{MWh_t}$/MWh].
$CNsu_{g,su} \in \mathbb{R}^+$	Start-up consumption of generator g for start-up type su [$\mathrm{MWh_t}$].
$CNsd_{gts} \in \mathbb{R}^+$	Shut-down consumption of generator g [$\mathrm{MWh_t}$].
$\overline{P}_g \in \mathbb{R}^+$	Maximum power output of generator g [MW].
$\underline{P}_g \in \mathbb{R}^+$	Minimum power output of generator g [MW].
$TmnS_{g,su} \in \mathbb{Z}^+$	Minimum downtime of generator g for start-up type su [h].
$IS_g \in \mathbb{B}$	Initial commitment status of generator g.
$IP_g \in \mathbb{R}^+$	Initial power output over $\underline{P}_g$ of generator g [MWh].
$TUo_g \in \mathbb{Z}^+$	Time that generator g has been on before the optimization period [h].
$TDo_g \in \mathbb{Z}^+$	Time that generator g has been down before the optimization period [h].
$TmnOff_g \in \mathbb{Z}^+$	Minimum downtime of generator g [h].
$TmnOn_g \in \mathbb{Z}^+$	Minimum uptime of generator g [h].
$RU_g \in \mathbb{R}^+$	Ramp-up rate of generator g [MW/h].
$RD_g \in \mathbb{R}^+$	Ramp-down rate of generator g [MW/h].
$TSU_g \in \mathbb{Z}^+$	Start-up time of generator g [h].
$TSD_g \in \mathbb{Z}^+$	Shut-down time of generator g [h].
$PSU_{g,tu} \in \mathbb{R}^+$	Power output of generator g at step tu of the start-up trajectory [MW].
$PSD_{g,td} \in \mathbb{R}^+$	Power output of generator g at step td of the shut-down trajectory [MW].
$TxE_g \in \mathbb{R}^+$	Generation tax per energy produced [€/MWh].
$TxI_g \in \mathbb{P}$	Generation tax per income [p.u.].

$TxC \in \mathbb{P}$	Generation tax common to all technologies [p.u.].
$TxCN_g \in \mathbb{R}^+$	Fuel tax [€/$\mathrm{MWh_t}$].
$TxCO2 \in \mathbb{R}^+$	CO_2 tax [€/ton].
$CO2r_g \in \mathbb{R}^+$	CO_2 emission ratio [ton/$\mathrm{MWh_t}$].
$PCN_g \in \mathbb{R}^+$	Fuel price [€/$\mathrm{MWh_t}$].
$TrefOn_g \in \mathbb{Z}^+$	Number of hours of the reference generation profile [h].
$PrefOn_{g,tr} \in \mathbb{R}^+$	Output power in each time step of the reference generation profile [MWh].
$CSteo_g \in \mathbb{R}^+$	Cost of generating power using the reference generation profile [€].

Chapter 1

Introduction

1.1 Introduction

Climate change is one of the most significant challenges of the 21$^{\text{th}}$ century. Its worldwide effects include such severe and worrisome problems as the melting of the polar ice shields that results in a sea-level increase, the increase in extreme weather events such as rainfall and floods in some regions, and the rise in heat waves, droughts, and wildfires in others (European Commission, 2022b). It is estimated that the economic consequences if the current trajectory is maintained could be an 11-14% global Gross Domestic Product (GDP) loss by 2050 (Swiss Re Institute, 2021). At the international level, 191 countries plus the European Union (EU) have committed, in the Paris Agreement (United Nations, 2015), to reduce greenhouse emissions to limit global warming to well below 2ºC (preferably 1.5ºC) compared to pre-industrial levels.

In the case of Europe, the European Green Deal (European Commission, 2019) intends to transform the EU into a resource-efficient and competitive economy, ensuring three main objectives:

- No net emissions of greenhouse gases by 2050.
- Economic growth decoupled from resource use.
- No person and no place left behind

This deal is an integral part of this Commission's strategy to implement the United Nation's 2030 Agenda and the sustainable development goals. Regarding greenhouse emissions, the European Commission has also set an intermediate objective to be met by 2030 to reduce 55% emissions compared to 1990 levels (European Commission, 2020).

The energy sector will play a vital role in this decarbonization, as it is responsible for 73.2% of the total emissions (Ritchie & Roser, 2020). Specifically, power generation is the largest carbon emitter, creating around 40% of global energy-related emissions (International Energy Agency (IEA), 2020). Increasing penetration of Renewable Energy Sources (RES) requires the support of dispatchable generators to cope with the inherent variability and uncertainty of wind and solar generation. Despite the technological improvements of storage systems (such as Na-ion, Li-S, and solid-sate batteries), or the potential increase of the round-trip efficiency of Power-to-Gas (P2G) systems, conventional generation will still be needed in the coming decades. In this context, although according to the International Energy Agency (IEA) (International Energy Agency (IEA), 2022b) coal and nuclear plants still represent the 44% and 13% of the total power generation, they are being questioned in many power systems worldwide due to environmental concerns. By contrast, Gas Fired Units (GFUs), such as Combined Cycle Gas Turbines (CCGTs), exhibit a better performance in terms of efficiency when compared to coal plants (58% for CCGTs vs 36% for coal plants (Naturgy, 2020)), and in terms of flexibility when compared to nuclear plants. Therefore, GFUs are expected to play an important role in the decarbonization process of the power sector during the following years.

The European Commission approved on 9 March 2022 a Complementary Climate Delegated Act (European Commission, 2022a) proposing that certain nuclear and gas activities fit in the Taxonomy Regulation category of transitional activities. Those activities cannot yet be replaced by low-carbon economically and technologically feasible alternatives, and are considered to contribute to climate change mitigation and to have the potential to play a major role during the transition to a net-zero emission economy. After the Parliament rejected the motion to oppose such consideration regarding gas and nuclear activities on 6 July 2022, the Taxonomy Delegated Act will enter into force as of 1 January 2023.

1.2 Decision making processes for GenCos

One of the challenges problem faced by a Generation Company (GenCo) is that it should try to maximize its expected long-term profit through the daily bidding procedure. However, formulating the overall long-run profit maximization problem by considering in detail the system's operation and its competitors' strategies would lead to a computationally unsolvable problem.

A well-established solution is to embed this decisions into a multi-level hierarchical organization of the scheduling optimization models (García-González, 2000). This hierarchy is usually defined in terms of the time scope of the decision variables involved, so that the solutions from higher-order models can be fed into lower-order models to avoid myopia in short-term decisions.

Regarding what is considered short, medium, and long term in this thesis, the long term is used for periods of several years, the medium term is around one year, and the short term refers to daily to monthly periods. Operation planning models are used for short and medium-term periods, whereas expansion planning models are for the long-term. These expansion planning models are used to plan investments in upgrading generation assets or building new facilities and are outside the scope of this thesis.

It is also worth noting that apart from the planning models, forecasting models are also needed to generate possible scenarios to be used as input data by the operating models. These models cover, for example, hydro input scenarios, prediction of electricity prices or residual demand curves, fuel prices, and renewable generation.

1.2.1 Hierarchical organization

GenCos are responsible for planning the operation of their generation resources. This planning involves decisions over variables with different time scopes that can be coupled along periods of greater or lesser duration. Thus, for example, in the long term, there is an inter-annual coupling in the management of the nuclear fuel cycle and the policy for using multi-year reservoirs. In the medium term, there is an intra-annual coupling in scheduling maintenance cycles, managing annual water reservoirs, or contracting Third Party Access (TPA) to the gas network. In the short term, the hourly scheduling and startup and shutdown decisions couple the periods of the day or week.

The main outputs of these models can be summarized as follows:

1. Medium-term operation model: produces inputs for the short term, such as the unavailability of the units under maintenance or the water value curves.
    - Information on the unavailability of the units under maintenance: when the company plans the maintenance of its plants, it does so with a long-term vision, trying to minimize the counterproductive effect of shutting down its plants.
    - Medium-term fuel consumption: the GenCo uses this data to make long-term bilateral contracts.
    - Water value curves: water is a resource that can be stored in reservoirs, so the company faces the problem of deciding how much water to consume in the short term and how much to store for the future. Such information can only be provided by the medium-term model and is typically given in the form of water value curves that relate the final reservoir level to the expected future profit.
2. Weekly (or monthly) operation model: plans the operation in the short term. Such planning allows the company to decide which units to start-up/shutdown, the monthly/daily TPA capacity to be contracted, and the management of the water reservoirs. In addition, as a by-product, an initial estimate of the expected hourly schedule of each generation unit is also provided. The main set point produced are:
    - Unit Commitment (UC) for the thermal units.
    - TPA contracting for the GFUs.
    - Amount of water to be released during the day.

3. Daily operation model: takes as input data the results of the weekly model and plans the optimal daily scheduling. This model benefits from having less computational burden due to a reduced horizon. In this way, it can increase the complexity of other issues such as improving the market revenue representation.

4. Day-ahead market bidding model: uses the UC, and the scheduling proposed from the daily model as inputs and uses them to generate the offers for the day-ahead market. These offers must optimize the GenCos' results complying with the market rules in force.

This models' hierarchical organization is summarized in Figure 1.1. As far as this thesis is concerned, it will focus on short-term planning models. These short-term models use data from forecasting and long-term planning models without going into too much detail about how they have been generated. The proposed outputs are the UC and the thermal unit program, without considering how these programs are converted into market offers, leaving the strategic bidding problem out of the scope of this thesis.

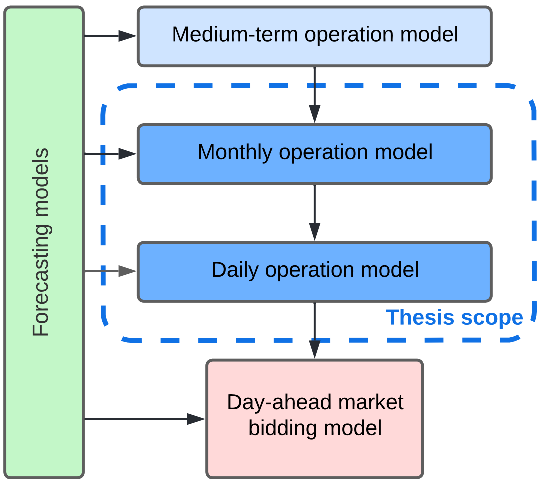


Figure 1.1: Optimization models hierarchy.

1.3 Natural gas sector

Besides the human tragedy it caused, the COVID-19 pandemic had a significant impact on the global economy and thus also led to a decline in global gas usage, which had been steadily increasing worldwide in previous years. However, as the health crisis is considered to be over and the world regains its activity, the gas sector is also experiencing a solid recovery. According to the IEA (International Energy Agency (IEA), 2022a), on the one hand, natural gas consumption increased by 4.6% worldwide in 2021, which is twice the decrease experienced in 2020. On the other hand, long-distance and Liquefied natural gas (LNG) trade raised by almost 10% in 2021.

This section presents a general overview of the gas sector, starting with the interaction between the gas and power systems, continuing with an illustrative description of the gas system, and ending with possibilities to acquire gas that the GenCos have.

1.3.1 Power and gas networks interaction

Although the power and gas systems share some similarities, such as the existence of a generation activity that, combined with possible imports/exports, supplies a demand using a transmission network, it is essential to understand their main differences and the elements linking both systems.

Regarding the differences, the most important ones are the storage and transmission speed. Whereas electric power is transmitted almost instantaneously and has a response time of seconds, gas flow through pipelines is slower with a maximum speed of around 15m/s (Gallagher, 2013), resulting in longer response times of hours. For that reason, typically in short-term models, electricity is planned with hourly time steps, whereas daily time steps are usually used for gas. Regarding storage, on the one hand, in the power system there is not intrinsic storage and in general the generation must match the demand. It is possible to use batteries or water reservoirs as storage, but its capacity is minimal compared to the overall volume. On the other hand, in the gas network, there exist storage facilities that are capable of storing huge volumes. Furthermore, it is even possible to use the gas network itself for short-term storage and provision of flexibility by using what is called linepack (Schwele et al., 2019), which consists of increasing the pressure in the pipes to store more gas inside them.

A schematic representation of the interaction between the two networks is shown in Figure 1.2.

Regarding the interaction between both gas and power systems, the main elements are the following:

- Compressor stations: The gas flows through the network pipelines due to the pressure difference of the nodes, from higher to those lower pressure nodes. The compressor stations are the elements that regulate such pressure differences to ensure that the gas flows to the required nodes. Compressors function using natural gas (directly taken from the pipeline flow) or electricity, in which case they represent an interaction element between the two networks.
- Gas-fired units: these are electric power generators that use gas as fuel. Common examples of these units are the CCGTs.
- Power to gas: a process of using electricity to produce gas. It may consist of two phases. For the first phase, an electrolyzer uses electricity to generate hydrogen from water. For the second phase, hydrogen and more electricity are used to produce methane or synthetic gas. On the one hand, hydrogen can be injected directly into the gas network but in limited quantities, because it alters the gas composition. On the other hand, methane and synthetic gas are fully compatible

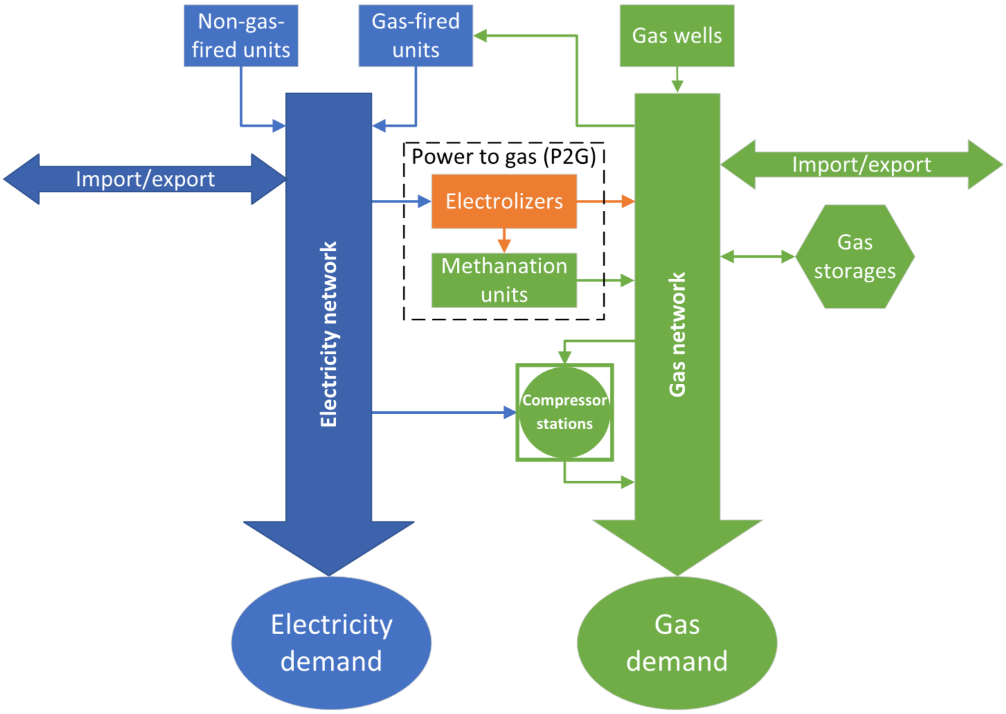


Figure 1.2: Power and gas networks interaction.

with natural gas, and there is no limit to the amount that can be injected. The typical efficiency of this type of installation is 54-77% for hydrogen and 49-65% for methane (Jentsch et al., 2014).

1.3.2 Gas sector general description

According to the Spanish gas System Operator (SO) Enagas, the definition of the gas system is the following (Enagas, 2022):

Spanish (original):

> "*Sistema Gasista: Conjunto de infraestructuras que lo forman, comunicadas entre sí y que permiten trasladar el gas natural desde los puntos de entrada (aprovisionamiento, oferta) a los de salida (consumo, demanda). Por lo tanto, resulta de combinar varios tipos de infraestructuras, cada una de ellas con sus características propias y condiciones particulares de funcionamiento.*"

English:

> "*Gas System: A set of interconnected infrastructures that allow the transfer of natural gas from the entry points (supply) to the exit points (consumption, demand). Therefore, it is the result of combining several types of infrastructures, each with its own characteristics and particular operating conditions.*"

Therefore, the gas system is a system that allows natural gas to be transported from generators/imports to consumers. Figure 1.3 shows a schematic representation of the essential elements present in these systems. This figure has a strong resemblance to the Iberian Peninsula; however, the representation of the components is illustrative and bears no real relation to the existing infrastructure in Spain and Portugal. There are several options for gas supply. On the one hand, there can be gas generation in the system itself. This gas is extracted from the natural reserves and injected directly into the transport network pipelines. On the other hand, gas can be imported directly through international pipeline connections or transported by LNG carriers. In the case of maritime transport, the vessels are filled in the origin system through a liquefaction plant, which pressurizes the gas to a liquid state to maximize the amount transported, and is then injected into the destination system using a regasification plant. Once in the system, the gas is transported through a transport network and local distribution networks from the entry points to the exit points. The movement of gas within the pipelines occurs from higher pressure areas to lower pressure areas. Therefore, compressor stations are used to regulate gas quantities and velocities through the pipeline during the system operation. In addition, the SO may also offer storage options for gas in LNG or underground storage facilities. Regarding the demand side, clients extract the gas from the exit points where they are located. A possible type of customer would be a GenCo that has CCGTs, connected both to the power network where they inject the generated electricity and to the gas network from where they extract the fuel they need. According to the example in figure 1, there is a power plant with two CCGTs located in point A and another plant with three CCGTs at point B.

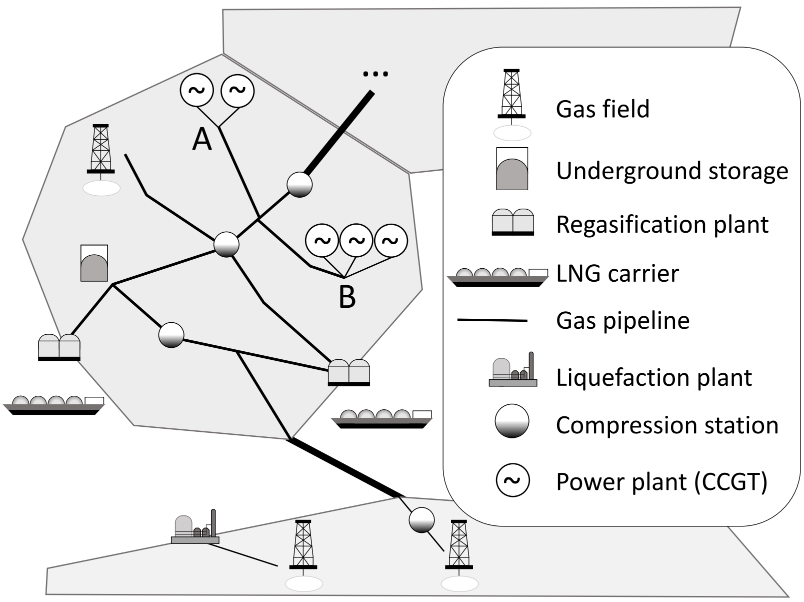


Figure 1.3: Generic gas system schematic representation.

In the past, it was the norm for systems involving networks, such as the gas, power, or railway systems, to be operated by vertically integrated companies. For example, in the power system, the same company that generated the electricity was usually responsible for the expansion, maintenance, and operation of the transmission and distribution networks and sold the electricity to end customers. These companies were often closely related to the government if not directly having public ownership. In those countries where liberalization processes of systems involving networks have taken place, competition has emerged at different levels. However, the network operation is considered a natural monopoly. Competition in network management would lead to its duplication, which is highly inefficient. Therefore, those vertically integrated companies that managed the networks have had to be unbundled, so that the operation of the network remains in the hands of an independent Transmission System Operator (TSO)[1]. This TSO has the exclusive right to expand, operate and maintain the network. However, it must offer its services to the different agents in a non-discriminatory manner and charge them adequately in order to recover its costs. Of course, not all countries have undergone such liberalization processes. For example, Russia still does not have a fully liberalized market. The major TSO Gazprom is also a producer and sells to end customers, and even though it has to offer pipeline usage to other players in the domestic market, it has a complete monopoly over gas exports (Mikulska, 2020). Furthermore, the fact that it is a natural monopoly does not mean that there is only one operator in each country. For example, there are two TSOs in Spain (Enagas and Reganosa) but in different geographical areas, so each operator has a monopoly in a specific area. For the two systems studied in this thesis, regarding the power system, (Joskow & Tirole, 2000) shows that inefficiencies would arise in an importing region where a generator has physical rights to the network because this increases its market power. With respect to the gas industry, (David & Percebois, 2002; Miguel Vazquez & Glachant, 2012; Newbery, 2002) highlights the relevance of network access for market development. The authors in (Xu et al., 2017) studied the case of China and showed that if they adopted an approach of letting an independent operator manage the network and establish TPA, overall flow optimization would improve social benefit.

This thesis focuses on liberalized markets such as those in the EU, some states in the United States of America (USA), Australia or United Kingdom (UK), among others. The legislation studied in detail is that of the EU, where Spain is used as example. In particular, in Europe, the implementation of the Internal Market In Natural Gas (IMING) started in 1999 and has been gradually progressing. Regarding this matter, in 2007 the Commission of the European Communities emphasized the need for an integrated and competitive gas market within the Community (Commission of the European Communities, 2007a).

Communications of the Commission of 10 January 2007 titled *'Prospects for the internal gas and electricity market'* (Commission of the European Communities, 2007c) and *'Inquiry pursuant to Article 17 of Regulation (EC) No 1/2003 into the European gas and electricity sectors (Final Report)'* (Commission of the European Communities, 2007b) demonstrated that rules and measures of the time did not offer the proper framework for the "creation of interconnection capacities to achieve the objective of a well-functioning, efficient and open internal market".

[1]TSO: "natural or legal person who carries out the function of transmission and is responsible for operating, ensuring the maintenance of, and, if necessary, developing the transmission system in a given area and, where applicable, its interconnections with other systems, and for ensuring the long-term ability of the system to meet reasonable demands for the transport of gas" (European Parliament and Council of the European Union, 2009a)

Based on this situation, Regulation (EC) nº 715/2009 (European Parliament and Council of the European Union, 2009b) came to light two years later. It set non-discriminatory rules for access conditions to: natural gas transmission systems, LNG facilities, and storage facilities; considering national and regional unique characteristics to ensure proper IMING functioning.

In order to achieve that objective, the regulation included harmonized principles for tariffs (or calculation methodologies) to access the network (but not to storage facilities), TPA services and capacity allocation and congestion-management principles, balancing rules and the corresponding imbalance charges, and capacity trading assistance.

This regulation also established the transmission system of the IMING as an entry-exit system. In this type of systems, users can inject gas into the network through an entry point and extract it from any exit point disregarding the path that gas follows through the network. The TSO manages the network in the most efficient way. This mechanism allows entry and exit services to be contracted independently. 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. Furthermore, each SO (transmission, storage, or LNG) must facilitate in a non-discriminatory and transparent manner the trade of such capacity rights.

1.3.3 Gas acquisition

The natural gas market is divided into the upstream sector (production countries) and downstream sector (countries where gas is consumed). The downstream industry includes supply, transportation, and distribution.

The way in which GenCos acquire gas to be burnt at their GFU plants is either through bilateral contracts with gas suppliers or by participating as buyers in gas spot markets. If they purchase gas from the spot market, they only need to pay the third-party access tariffs corresponding to infrastructure use at exit points where gas is delivered. If they acquire gas using bilateral contracts, the process is dependent on the requirements established in the contract and delivery point conditions. If the gas is delivered in a regasification terminal, the terminal must inject the gas into the network, and corresponding tariffs must be paid. If the gas enters the system through an international connection, corresponding usage fees also must be taken into account. In an entry-exit model, gas is not actually transported from the entry point to the exit point, but same gas amount is injected/extracted to/from the network at the entry/exit points. Therefore, once gas enters the network, there are two possibilities: 1) using it straight away by moving it through the network to the power plant that will consume it or 2), storing it for future use. Nonetheless, even though a GenCo is expected to purchase gas for its generation needs, it can also resell the gas through bilateral contracts or in the spot market.

Traditionally, bilateral contracts have amounted to the majority of the gas traded (Asche et al., 2013; Rey, 2017). In the EU such contracts still represent a major part in gas trading; however, spot markets are gaining weight and are being promoted through directives, which are part of *'Energy Packages'*, to establish a fully integrated energy market. Gas spot markets are organized as virtual gas trading points associated with input-output zones called hubs. According to (Heather & Petrovich, 2021), the most important European hubs that can be considered mature are the Dutch TTF and the British NBP. With lower trading volumes, considered active although not yet mature due to lack of liquidity, are the German THE (resulting from GPL and NCG merge), the Italian PSV, and the Austrian VTP. Finally, there are five poorly developed hubs, TRF in France, PVB in Spain, ZEE-ZTP in Belgium and Luxembourg, and VOB in the Czech Republic. Figure 1.4 shows the evolution of trading volumes in European hubs.

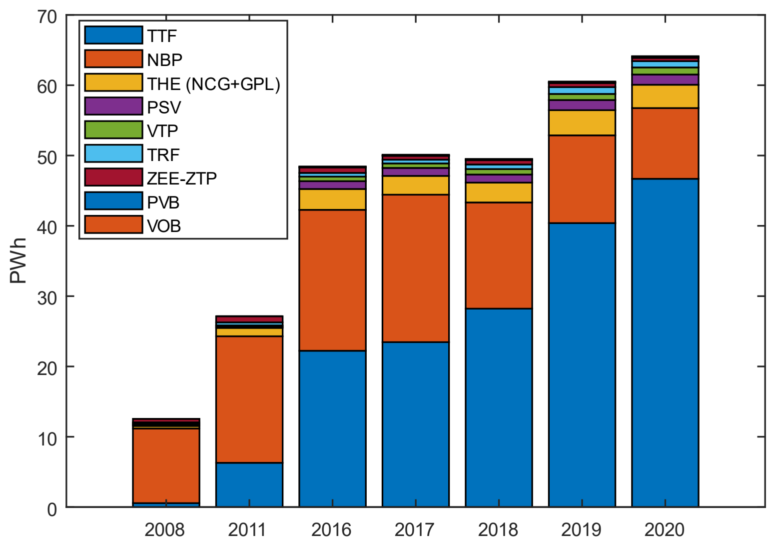


Figure 1.4: Traded volumes in European gas hubs.

Bilateral gas contracts have been usually indexed to oil or oil derivatives prices, as they were substitute energy resources in many cases (Dueñas et al., 2012; Stern & Rogers, 2011). Since bilateral agreements have dominated gas markets, some studies account for them when performing optimizations on the power system. The authors in (Dueñas et al., 2012), for example, presents common possible conditions for long-term contracts and integrates a model to manage gas contracts with a medium-term electricity market equilibrium model. Regarding the price correlation, until 2008, most of the long-term gas contracts made in Europe were based on oil products. However, motivated by the increase in traded volumes, the decrease in actual oil-gas resource substitution, and the 2008 crisis, oil and gas prices started to lose correlation (Stern & Rogers, 2011). Since then, gas prices have become more hub-related.

1.4 Third Party Access regulation

Section 1.3.2 Gas sector general description explained the gas system elements. Furthermore, that section also highlighted the need for specific infrastructures, such as the transmission network, not to be open to competition (by geographical areas) in order to maximize the investment efficiency. For this reason, an independent SO should be in charge of certain types of infrastructure, having a monopoly over them. This SO must guarantee non-discriminatory access to the different agents that want to use that infrastructure. In addition, the SO must apply a charging system to recover the expansion, maintenance, and operation costs. These types of charges levied on agents wishing to use the infrastructure are usually called TPA tariffs. This tariff system is used in several countries such as USA (International Energy Agency (IEA), 2019), Australia (Council of Australian Governments, 2003), Malaysia (Parliament of Malaysia, n.d.), those in the EU, or UK (from when it was part of the EU). This section will explain how these TPA work in the EU environment.

Commission Regulation (EU) No 984/2013 of 14 October 2013 (European Commission, 2013) (which became effective on 1 November 2015) established a network code on capacity allocation mechanism in gas transmission systems aimed to achieve harmonization across the EU. This regulation's implementation relied on tariff systems that ensured that TSOs revenues were not adversely affected. That regulation was repealed on 8 April 2017 by Commission Regulation (EU) 2017/459 of 16 March 2017 (European Commission, 2017a), which established a network code on capacity allocation mechanisms in gas transmission systems, consistent with the previous regulation. The regulation defines gas periods that do not coincide with natural calendar periods: gas years start on 31st October; gas quarters start on 1st October, 1st January, 1st April and 1st July respectively; gas months start the 1st day of each calendar month; gas days start at 5:00 Universal Coordinated Time (UTC) during wintertime and 4:00 UTC during summertime; and within-day products go from the time they are being contracted to the end of the corresponding gas day. It is important to note that these gas periods are not synchronized with the day-ahead electricity market.

Regarding capacity products, it is important to consider the different time horizons of the available products. In that sense, yearly, quarterly, monthly, daily, and intra-day capacity products are offered. Reference prices are established for yearly periods, and those of shorter durations have penalizations. Therefore, from the point of view of a GenCo, all products should be considered. However, when should the GenCo consider these products is also essential. When looking at the long term, yearly and quarterly products must be considered, but when operating in the short term, as the focus of this thesis, such contracts have to be assumed as decisions already taken, and only the short-term products have to be considered.

In conformity with Regulation (EC) No 715/2009, Commission Regulation (EU) 2017/460 (European Commission, 2017b) established a network code on harmonized transmission tariff structures for gas. It set out the requirements for publishing the information related to the determination of the revenues of TSOs and the generation of different transmission and non-transmission tariffs. Since the transmission system is an entry-exit system, transmission costs are not strictly related with the specific path from entry to exit points, and entry/exit services can be contracted separately. For that reason, transmission tariffs have to be based on a reference pricing methodology that uses specific cost drivers to guarantee a sufficient level of cost reflectivity and predictability in the system. The operation cost of the services offered by the TSO have to be collected by means of capacity-based and commodity-based (exceptionally) transmission tariffs. With capacity tariffs, the agents acquire the rights to use the entry/exit access points while the commodity tariffs are paid for the actual usage of those access points. On the one hand, the portion of the transmission services cost to be recovered by capacity-based transmission tariffs are determined according to one of the following options:

- Technical capacity.
- Forecasted contracted capacity.
- Technical capacity and distances.
- Forecasted contracted capacity and distances.

On the other hand, the part of the cost to be recovered by commodity-based transmission tariffs are based on one of the following concepts:

- Gas flow amounts.
- Gas flow amounts and distances.

As mentioned before, a reference price methodology should be determined by the national regulatory authority for all entry and exit points of its entry-exit system (there could be several methodologies in case more than one transmission system operator is active). That reference price methodology has to allow network users to replicate reference prices calculation and forecasts. If the methodology applied is not the capacity weighted distance reference price methodology (expressed in (1.1) and (1.2)), the proposed methodology should use the latter as a counterfactual.

$$AD_{en} = \frac{\sum_{ex} [CAP_{ex} \cdot D_{en \rightarrow ex}]}{\sum_{ex} [CAP_{ex}]} \tag{1.1}$$

$$T_{en} = \frac{R_{Ten} \dfrac{CAP_{en} \cdot AD_{en}}{\sum_{en} [CAP_{en} \cdot AD_{en}]}}{CAP_{en}} \tag{1.2}$$

$en \in EN \subseteq X$ 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 prices for interruptible capacity have discounts calculated according to Directive 2009/73/EC (European Parliament and Council of the European Union, 2009a). Alternatively, in points that suffered physical congestion the previous year, an ex-post compensation could be applied. The ex-post compensation to be paid is three times the price of daily firm capacity for each day there is an interruption.

The following is an illustrative example of how to implement the previous methodology. The simplified system used is the one presented in Figure 1.5. Both regasification plans are considered entry points, and the exit points are the CCGTs located at A and B.

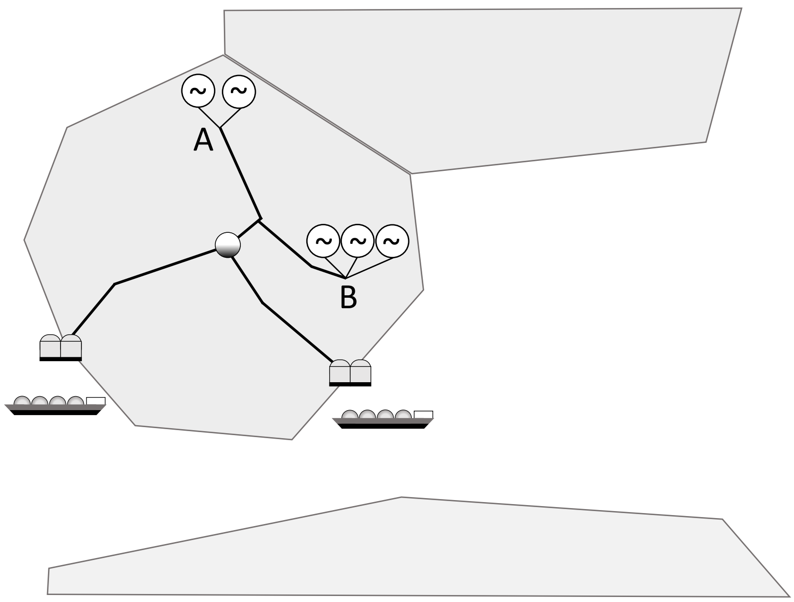


Figure 1.5: TPA tariff calculation from entry to exit points.

The calculations to compute the tariffs at entry and exit points are displayed hereafter:

- $CAP_{enEast} = 4TWh/year$
- $CAP_{exA} = 2TWh/year$
- $CAP_{enWest} = 1TWh/year$
- $CAP_{exB} = 3TWh/year$

- $D_{enEast \to exA} = 240km$
- $D_{enEast \to exB} = 230km$
- $D_{enWest \to exA} = 260km$
- $D_{enWest \to exB} = 250km$

$$AD_{enEast} = \frac{2 \cdot 240 + 3 \cdot 230}{2 + 3} = 234 \qquad T_{enEast} = \frac{R_{Ten} \frac{4 \cdot 234}{4 \cdot 234 + 1 \cdot 254}}{4} = \frac{0.1966 \cdot R_{Ten}}{TWh}$$

$$AD_{enWest} = \frac{2 \cdot 260 + 3 \cdot 250}{2 + 3} = 254 \qquad T_{enWest} = \frac{R_{Ten} \frac{1 \cdot 254}{4 \cdot 234 + 1 \cdot 254}}{1} = \frac{0.2134 \cdot R_{Ten}}{TWh}$$

$$AD_{exA} = \frac{4 \cdot 240 + 1 \cdot 260}{4 + 1} = 244 \qquad T_{exA} = \frac{R_{Tex} \frac{2 \cdot 244}{2 \cdot 244 + 3 \cdot 234}}{2} = \frac{0.2050 \cdot R_{Ten}}{TWh}$$

$$AD_{exB} = \frac{4 \cdot 230 + 1 \cdot 250}{4 + 1} = 234 \qquad T_{exB} = \frac{R_{Tex} \frac{3 \cdot 234}{2 \cdot 244 + 3 \cdot 234}}{3} = \frac{0.1966 \cdot R_{Ten}}{TWh}$$

With the obtained results, of the total cost to be recovered by the capacity-based tariffs at entry points (R_{Ten}), the East point will be charged a 19.66% per each TWh injected and the West point a 21.34%/TWh. Regarding the cost to be recovered by the exit point (R_{Tex}), points A and B will have to pay 20.50%/TWh and 19.66%/TWh respectively.

1.5 Taxes involved in electricity generation

Energy, climate and water taxes or charges are expected to become much more relevant in the future, given the need to decarbonize energy and power systems, and to strive towards their sustainability (David M., 2005). Carbon taxes are already present in many regions, as well as energy taxes or water charges. However, their impact will depend on how they are implemented: in some cases (e.g. carbon taxes) they change marginal costs, in others (e.g. water charges, or paying for technology support) they may be even fixed amounts, not related to the energy produced. Windfall taxes, which are higher tax rates on profits that ensue from sudden windfall gains to a particular activity, are also being considered in some markets. When affecting variable costs, these taxes will in turn change optimal operation depending on how GenCos are able to pass them through in their market bids (Sijm et al., 2006). 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. Although there are many ways in which taxes can be used in the power sector (see e.g. (David M., 2005) for an extensive review), the following are the main categories:

- 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).

In practice, it could be the case that legal figures other than taxes are used. For example, Spain is within the European framework; therefore, GenCos must acquire CO_2 emission rights corresponding to the emissions they cause. When considering these emission rights in the companies' accounting, they are considered as "intangible assets". When they are used, they have to be regarded as expenses that do not fall within the specific "taxes" category. The correct categorization within the bookkeeping depends on the country and is beyond this thesis's scope. Furthermore, the category assigned is irrelevant from the mathematical perspective. Thought this thesis we are not going to focus in these legal particularities, therefore we will use the term "tax" for CO_2 emissions related expenses.

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 generation expenses 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 (Díaz et al., 2019). Therefore, a correct representation of these different taxes is essential to understand their impact on the power system's operation.

1.5.1 The Spanish case

In this section, the taxes that affect the Spanish market are detailed. In this way, a real case is presented as an example, and those taxes that will be taken into account in Chapter 4 Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology are introduced.

The following are all the national taxes that apply to electricity generation. They are categorized by what they charge, and if there is more than one tax levied on the same concept, they are separated according to their nature.

- Fuel consumption: *'Law 38/1992, of December 28, 1992, on Excise Taxes'* [2] (Jefatura del Estado, 1992) imposed a charge on the use of fossil fuels. In the case of electricity generation, this charge affects plants whose fuel is coal or gas. Since then, there have been periods when certain activities have enjoyed tax exemptions following the different policies that have been implemented. Regarding electricity generation plants, they are currently exempt from such charges since the approval of the *'Royal Decree Law 15/2018'* [3] (Jefatura del Estado, 2018). However, it is essential to bear in mind that such exemption might not be permanent, and it is advisable to model.

- Greenhouse gas emissions: As a member of the EU, Spain is subject to the same regulations on emissions. This regulation, in force since 2005, uses the *'polluter pays'* principle (European Parliament and Council of the European Union, 2004) so that activities that generate CO_2 emissions must purchase CO_2 emission rights. A certain number of CO_2 emission allowances are put into circulation through auctions every year. The EU sets a cap on the number of allowances to be auctioned, lower each year, in line with the decarbonization targets. After auctioning by the EU, there are markets in which the various agents can buy and sell the allowances.

- Revenues from electricity generation:

  - Impuesto sobre el Valor de la Producción de la Energía Eléctrica (IVPEE) [4]: *'Law 15/2012, of December 27, on fiscal measures for energy sustainability'* [5] (Jefatura del Estado, 2012) introduced the IVPEE, a 7% tax on electricity generation revenues. The last year 2021 it was temporarily suspended in *'Royal Decree-Law 12/2021, of June 24, adopting urgent measures in the field of energy taxation and matters of energy generation, and on the management of the regulation fee and the water use tariff'* [6] (Jefatura del Estado, 2021) to help temporarily alleviate the increase in the rise of electricity prices. However, it is currently in force.

[2] Original: Ley 38/1992, de 28 de diciembre, de Impuestos Especiales.
[3] Original: Real Decreto Ley 15/2018.
[4] Translation: Tax on the Value of Electric Energy Production.
[5] Original: Ley 15/2012, de 27 de diciembre, de medidas fiscales para la sostenibilidad energética.
[6] Original: Real Decreto-ley 12/2021, de 24 de junio, por el que se adoptan medidas urgentes en el ámbito de la fiscalidad energética y en materia de generación de energía, y sobre gestión del canon de regulación y de la tarifa de utilización del agua.

– Levy on the use of water: *'Law 15/2012, of December 27, 2012, on fiscal measures for energy sustainability'* [7] (Jefatura del Estado, 2012) amended article 112 of the *'Royal Legislative Decree 1/2001, of July 20'* [8] (Ministerio de Medio Ambiente, 2001) adding a 112 bis. This article established a *'fee for the use of inland waters to produce electricity'* [9]. Such tax was later amended by *'Royal Decree 198/2015, of March 23'* [10] (Ministerio de la Presidencia, 2015), and subsequently by *'Royal Decree-Law 10/2017, of June 9, adopting urgent measures to alleviate the effects produced by the drought in specific hydrographic basins'* [11] (Jefatura del Estado, 2017). The collection of said tax was recently annulled in 2021 by the Third Chamber of the Supreme Court [12] in several judgments (Tribunal Supremo, 2021a, 2021b, 2021c, 2021d, 2021e, 2021f, 2021g, 2021h, 2021i). This annulment was based on the fact that the concessions were not updated with this new tax. Therefore, although it is not currently being applied to any power plant, it is convenient to take it into account because it could be used in the future with the renewal of the concessions. The final version of the tax is as follows: 25.5% of operating profits, except in the case of power plants of less than 50 MW, which enjoy a 92% exemption, and in pumped-storage plants, where the discount is 90%. For calculating the tax in pumped-storage plants, only water that has been pumped is discounted, whereas to the generation that used water coming from natural watercourses, the entire charge is applied.

Spain is divided into seventeen autonomous communities and two autonomous cities. In terms of legislation, there are state regulations common to the whole country, and in addition, the autonomous communities can develop their own legislation for their territories. That is the case with energy taxation. As an example, the specific regulation for Catalonia is presented. This autonomous community has specific energy taxation regulation that adds to the state taxation in its territory. *'Law 5/2020, of April 29'* [13] (Comunidad Autónoma de Cataluña, 2021), amending *'Legislative Decree 3/2003, of November 4'* [14] (Comunidad Autónoma de Cataluña, 2003), established that the following taxes were applicable in the Catalonian territory:

– Electricity generation affecting the environment: the Catalonia government approved a tax on facilities that affect the environment. This tax is levied on all electricity generation activities with the following exceptions: generation for self-consumption; generation in slurry treatment or sewage sludge drying plants; solar, wind, hydraulic, and other renewable generation; generation from biomass or biogas; generation in high-efficiency co-generation facilities. The value of this tax 1 €/MWh for the specific case of CCGTs and 5 €/MWh for other non-exempt power plants.

[7] Original: Ley 15/2012, de 27 de diciembre, de medidas fiscales para la sostenibilidad energética.
[8] Original: Real Decreto Legislativo 1/2001, de 20 de julio.
[9] Original: canon por utilización de las aguas continentales para la producción de energía eléctrica.
[10] Original: Real Decreto 198/2015, de 23 de marzo.
[11] Original: Real Decreto-ley 10/2017, de 9 de junio, por el que se adoptan medidas urgentes para paliar los efectos producidos por la sequía en determinadas cuencas hidrográficas.
[12] Original: Sala tercera del Tribunal Supremo
[13] Original: Ley 5/2020, de 29 de abril.
[14] Original: Decreto Legislativo 3/2003, de 4 de noviembre.

– Levy on the use of water: The industrial use of water for electricity generation is charged at 6.08 €/MWh for GenCos with more than 50 MW installed capacity and 0.40 €/MWh for agents with less power installed.

1.6 Main objectives of this thesis

GenCos must plan the operation of their generation units, and when facing this task, the following question arises: are there aspects in the current regulation affecting the operation planning that the state-of-the-art models do not correctly consider and therefore require some adaptations?

This is the main research question that motivated this thesis, and to answer it, three main general objectives were proposed: 1) to study the regulation applicable to electricity generation activity and the implications it may have on planning models, 2) to propose improvements to self Unit Commitment (self-UC) models to properly take these issues into account, and 3) to study the relevance of correctly considering these aspects in the optimization models, and thus the need to use the improvements developed for the achievement of the second objective.

As will be seen in the following Chapter 2 State of the art, the current models do not include the particularities of the real systems that we have just detailed. From our experience, models without considering these issues do not offer the desired results in their practical application. In particular, the author has participated in several research projects with the objective of developing optimization tools to support the decision-making process of the energy management department of one of the most prominent Spanish utility companies. These projects covered the planning of all generation assets (thermal, hydro, and renewable) for the different markets (day-ahead, secondary reserve, and technical constraints). Thanks to this collaboration with the industry, he has had the opportunity to deal with day-to-day problems, some of which have motivated the issues covered in this thesis regarding the units' cost structure.

However, this thesis tries to be general and not just focus only on the problem faced by a GenCo in a particular country. For example, regarding the gas system, the modeling is based on European legislation, and the Spanish system is just the study case used to illustrate how the formulation works. Regarding the potential beneficiaries of the models developed in this thesis, on the one hand, there would be the GenCos themselves. On the other hand, there would also be regulatory entities and system operators to whom these same models would provide helpful tools to simulate and study the expected behaviors of the agents participating in the market.

The stated primary objectives can be disaggregated into the following secondary objectives for the self-UC problem:

- Consider the gas network TPA tariffs in a detailed manner for the CCGTs cost representation.

- Consider portfolio gas purchases in the gas spot market for all CCGTs operation.
- Develop an optimization model that determines the daily and monthly TPA optimal contracting.
- Model in detail the taxes and charges that affect the power generation activity.
- Design a correct representation of generation assets that have a shared ownership.
- Mitigate undesired behaviors that may arise to comply with regulation.

Lastly, we wanted to give some attention to the digitization, one of the indisputable current trends in the industrial sector. In this paradigm, the most common practice is outsourcing computing and information storage to servers and remotely accessing those services. For the context of optimization, this increases the possibilities by accessing servers with excellent computing power but incurring minimal costs since only the actual usage time is charged. In the projects developed for the industry where the Ph.D. student has participated, this has been the way of working: making optimization models ready to be deployed in cloud computing infrastructures. Taking advantage of all this acquired knowledge and trying to approach the research world to the leading-edge industry procedures, this thesis includes an example of a model implementation in a cloud computing infrastructure (Amazon Web Services (AWS)) that could inspire future researchers to take advantage of this promising technology.

1.7 Document organization

The structure of the thesis is as follows:

- Chapter 1: Introduction to the power and gas systems and some regulations affecting the power generation business.
- Chapter 2: State of the art review.
- Chapter 3: Modeling of TPA tariffs contracting and gas purchases at the portfolio level.
- Chapter 4: Modeling of individual income to correctly account for taxes and shared ownership of the different generation units.
- Chapter 5: Two modeling approaches to avoid strategic behaviors from profit maximization models in regulated markets.
- Chapter 6: Conclusions, contributions, and future research lines.

Those chapters represent the core of this thesis, where the main contributions have been made. In addition, the thesis includes three appendixes with additional material to make the document self-contained while trying to help the reader to distinguish the main ideas from other supplementary information:

- Appendix A: A detailed explanation of the stochastic formulation used in the self-UC presented in Chapter 3.
- Appendix B: A minor improvement to model the operating modes of CCGTs with different configurations of gas and steam turbines.
- Appendix C: An implementation guide to perform automatic executions of the optimization model in a production-level cloud infrastructure using AWS.

1.7.1 Combination and use of the models

Regarding the main modeling contributions, chapters 3 and 4 present improvements to increase the detail in which the cost structure (Chapter 3) and revenues for price-maker agents (Chapter 4) are considered. Additionally, Chapter 5 presents two alternative approaches for a competitive self-UC from the point of view of an individual agent, with one model whose objective is to maximize the agent's profit and another whose objective is to maximize social welfare. In the first two chapters, the improvements are illustrated with example cases in which the profit obtained by an agent participating in the market is maximized. However, these examples only demonstrate how the formulation works, and both the profit and the social welfare maximization approaches can include these formulations and benefit from their advantages. From the point of view of their usefulness, the models focus on the operation of individual market participants with the data they have available in realistic situations. Still, their use is not restricted to such agents; they are also very helpful tools for regulators or system operators, providing them with information on the expected behavior of the agents. Figure 1.6 summarizes this idea. It can be seen that developments from chapters 3 and 4 can be included in those of chapter 5 and that such models are helpful for GenCos, regulators, and system operators.

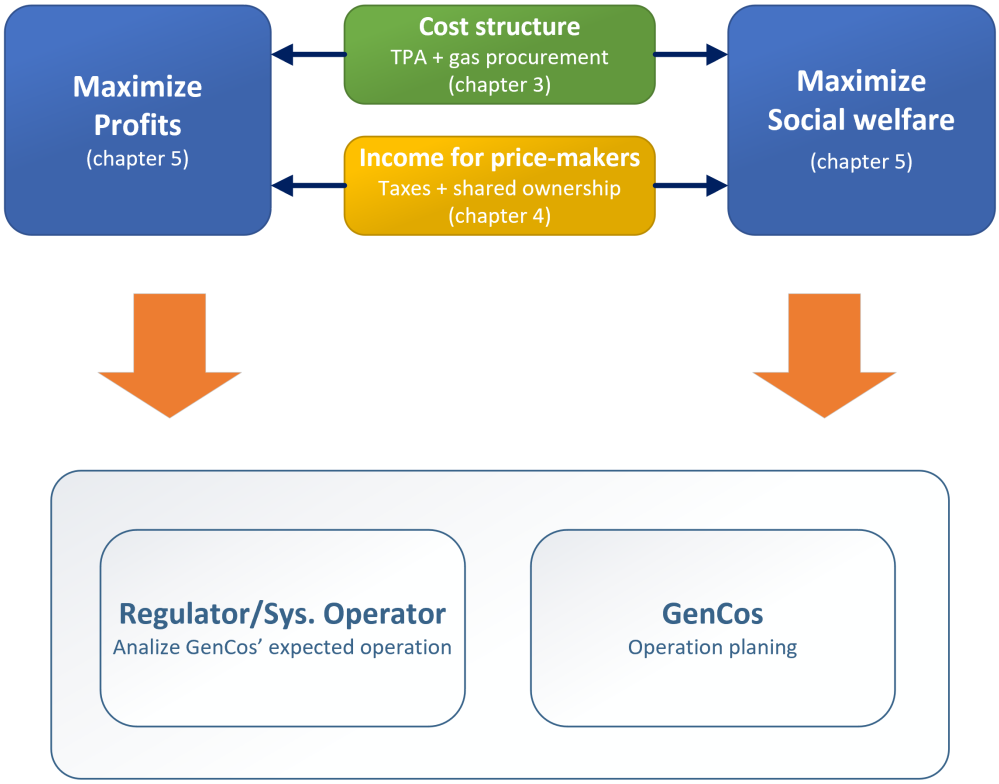


Figure 1.6: Combination and use of the models.

Chapter 2

State of the art

2.1 Introduction

This chapter reviews the state-of-the-art mathematical modeling of the self Unit Commitment (self-UC) problem. First, in Section 2.2 Modeler's perspective, the different perspectives that can be adopted depending on the model's target user are presented. Next, in Section 2.5 The Unit Commitment problem, we analyze how Unit Commitment (UC) can be modeled and how uncertainty is considered. In addition, a base UC formulation that will be improved throughout the thesis is presented. Subsequently, in Section 2.3 Electricity-gas interaction the analysis is focused on the interaction between power and gas systems. Section 2.4 Strategic behavior focuses on modeling the revenues of the generation units of an agent participating in the market. Finally, Section 2.6 Conclusions presents the conclusions based on this review and identifies the research gaps to be addressed in the following chapters.

2.2 Modeler's perspective

A crucial modeling aspect is the perspective taken when modeling the power system. In this respect, a distinction is made between two almost opposite views, the *operator's* and the *agent's perspectives.*

The *operator's perspective* corresponds to that of a System Operator (SO). This approach was the common paradigm before the liberalization of the electric power industry was implemented. In this case, the operator is interested in the viability and efficiency of the system. Therefore, it will aim to minimize operation costs or maximize social welfare, with particular emphasis on ensuring the security of the system. Its interest regarding the uncertainty treatment would be related to concepts such as grid congestions, contingencies, or renewable generation insofar as an alternative generation may be needed if there are changes concerning the forecasted weather. However, the *operator's* *perspective* is not exclusive to a centralized power system as the market-clearing algorithm can be designed analogously. For instance, the market-clearing of Midcontinent Independent System Operator (MISO) is formulated as an optimization model considering a very detailed representation of both the generation and transmission systems. Therefore, an example of the *operator's perspective* would be 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 (Manshadi & Khodayar, 2019; Zhao et al., 2017). 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 power and gas system as in (Correa-Posada & Sánchez-Martín, 2015b; Correa-Posada et al., 2017). In (C. Liu et al., 2015) the authors 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.

The *agent's perspective* is that of a Generation Company (GenCo) participating in the market. Its interest will be fundamentally economic, seeking to maximize its profit as in any other market. Its treatment of uncertainty will be related to uncertainty in electricity price predictions (which may be impacted by renewable generation) or generation costs affected, for example, by gas prices. The agents' interest regarding possible contingencies such as gas grid congestions will be related to their impact on costs. This approach has being developed since the beginning of the liberalization processes in the power and gas systems. The papers (Campos & Reneses, 2014; Sahin et al., 2011) 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 GenCo who is responsible for finding the optimal scheduling of its generators trying to maximize the expected profit. The term Profit Based Unit Commitment (PBUC) is usually used when the objective function consist in maximizing the profits of a market agent. A recent review specifically focused in PBUC models is presented in (Abdi, 2021), where the author says that the common approach consists in a GenCo acting as price-taker. However, in other works (García-González & Barquin, 2000) GenCos are considered price-maker agents.

Finally, there are models that try to simulate the behavior of rational agents competing in the market and subject to the interdependence of their actions. This would be a special category, the *market equilibrium* models, that is somehow in the middle of the *operator's and agent's perspectives*. These models can be focused in the electricity market (Kazempour & Hobbs, 2018a, 2018b) or in both the power and gas markets to have a better comprehension of the potential interactions between the gas and electricity markets as (Chen et al., 2020a, 2020b; Wang et al., 2018). These models can be used both with an *operator's perspective* by a SO to assess the market functioning in the presence of strategic agents, or with an *agent's perspective* by market participant to make coordinated operations in the electricity and natural gas markets, (Gil et al., 2016).

2.3 Electricity-gas interaction

The strong interlinkage between the natural gas sector and the electric power industry requires a coordinated planning and operation of their related infrastructures (Schwele et al., 2019), and a joint assessment of their market rules (Vazquez & Hallack, 2015). This section gives a general overview of the most common approaches regarding such interaction. Section 2.3.1 Gas network modeling presents the different strategies that are usually implemented to model the gas network, and later subsection Section 2.3.2 Coordination strategies between gas and power systems explains how the power and gas systems are optimized considering each other.

2.3.1 Gas network modeling

Natural gas is delivered from supply to consumption through a transmission network. In this subsection, four methods used to represent the gas network are presented. They are classified according to their main characteristics in Table 2.1.

Table 2.1: Pipeline gas flow modeling approaches.

Model	Gas inflow = outflow	Linepack	Formulation
Transport	Yes	No	Algebraic linear
Dynamic	No	Implicit	Nonlinear PDE
Steady-state	Yes	No	Algebraic nonlinear
Quasi-steady-state	No	Approximation	Algebraic nonlinear

2.3.1.1 Transport modeling

This model uses a simplified network system . It ignores the dynamics of the gas network and simply limits the amount of gas transported through the pipelines to a maximum amount per period (2.1) and per day (2.2). Such basic modeling can lead to far from feasible solutions, and therefore, it is rarely used.

$$q_{n,m,t} \leq \overline{Q^t_{n,m}} \tag{2.1}$$

$$\sum_{t \in \Omega^t_d} [q_{n,m,t}] \leq \overline{Q^d_{n,m}} \tag{2.2}$$

where:

t hours

d days

n, m gas network nodes

Ω_d^t hours t belonging to day d

$q_{n,m,t}$ gas flow from n to m in hour t

$\overline{Q_{n,m}^t}$ maximum hourly gas flow from n to m

$\overline{Q_{n,m}^t}$ maximum daily gas flow from n to m

A security constrained UC is presented in (T. Li et al., 2008). In (Qadrdan et al., 2010) the authors analyze the impact that a large amount of wind generation would have on the gas networks as Combined Cycle Gas Turbines (CCGTs) would be used to cover the uncertainty. The reference (Sahin et al., 2011) studies the impact of natural gas contracts and constraints on a GenCo's midterm scheduling using a stochastic price-based UC problem. A stochastic approach is presented in (Zhao et al., 2017) assuming that committed units in the first-stage can respond to real-time natural gas availability unveiled in the second-stage.

2.3.1.2 Dynamic modeling

Dynamic modeling uses a nonlinear and nonconvex Partial Differential Equations (PDEs) system to represent gas flows while respecting space-time couplings (C. Liu et al., 2011; Roald et al., 2020; Y. Zhou et al., 2017; Zlotnik et al., 2017). This type of modeling can simulate slow gas movement, and its results are pretty similar to the actual behavior of a physical system. The PDEs representing the gas flow dynamics are the following Euler equations: continuity, momentum, and energy conservation. However, the equations are not used directly, but rather a series of assumptions are usually made, and terms that do not significantly impact systems such as the gas transportation network are simplified. These assumptions are the following: The flow is assumed to be isothermal (Correa-Posada & Sánchez-Martín, 2014; C. Liu et al., 2011), and therefore the energy conservation equation is neglected; the force of gravity is ignored because of its negligible impact (C. Liu et al., 2011); gas inertia is overlooked against pressure gradients (Correa-Posada & Sánchez-Martín, 2014); finally, pipelines are assumed to be horizontal (Correa-Posada & Sánchez-Martín, 2014). Therefore, the simplified equations (2.3) and (2.4) are used to model the gas dynamics.

$$\frac{\partial p}{\partial t} + \frac{ZRT}{M_g}\frac{\partial f}{\partial x} = 0 \tag{2.3}$$

$$\frac{\partial p^2}{\partial x} + \frac{ZRT\lambda}{M_g D} f|f| = 0 \tag{2.4}$$

where:

t time

x pipeline axis direction

p gas pressure

D pipe diameter

λ pipeline friction factor

Z natural gas compressibility factor

R universal gas constant

T absolute temperature

Mg natural gas molecular weight

ρ natural gas density

u x-axis gas velocity

f specific mass flow rate (pressure times density)

The major problem of this modeling approach is its computational complexity (Zlotnik et al., 2017). When using this modeling, PDEs have to be spatially and temporally discretized. The techniques used are implicit (most common) and explicit finite-difference methods, and finite element methods (Behbahani-Nejad & Bagheri, 2010). Implicit methods are more usually implemented due to their performance (Clegg & Mancarella, 2015; Pambour et al., 2017).

2.3.1.3 Steady-state modeling

In the steady-state representation, the time derivatives are eliminated. Therefore, the inflow is assumed to be equal to the outflow. Applying a series of simplifications typical of high-pressure transport systems, the well-known Weymouth equation (2.5) is used. Equation (2.6) indicates the direction of flow from higher to lower pressure nodes. This equation can be linearized using binary variables with the big-M method (He, Liu, et al., 2017a; He, Wu, et al., 2017; Sundar et al., 2021). However, equation (2.5) remains nonlinear because of the squared pressures.

$$q_{n,m,t} = sgn\left(p_{n,t}, p_{m,t}\right) K_{n,m} \sqrt{\left|p_{n,t}^2 - p_{m,t}^2\right|} \tag{2.5}$$

$$sgn\left(p_{n,t}, p_{m,t}\right) = \begin{cases} +1 & if\ p_{n,t} \geq p_{m,t} \\ -1 & if\ p_{n,t} < p_{m,t} \end{cases} \tag{2.6}$$

$$q_{n,m,t}^{in} = q_{n,m,t}^{out} = q_{n,m,t} \tag{2.7}$$

where:

t time

n, m gas network nodes

$K_{n,m}$ Weymouth factor of pipe from n to m

$p_{n,t}$ gas pressure at node n at time t

$q^{in}_{n,m,t}$ inflow gas in pipe from n to m at time t

$q^{out}_{n,m,t}$ outflow gas in pipe from n to m at time t

$q_{n,m,t}$ average gas flow from n to m at time t

On certain occasions, the Weymouth (2.5) equation is simplified by making it unidirectional. This simplification eliminates the need for the (2.6) equation. However, for the operation of the gas transmission systems, it is necessary to take into account that changes in flow direction may occur. For example, the flows could vary in the case of needing to turn on several CCGTs due to a change in electricity demand or renewable generation. There are several approaches regarding the solution methods, for example, the direct solution of the nonlinear problem, the Newton-Raphson method, or piece-wise linearizations.

2.3.1.4 Quasi-steady-state modeling

In addition to the basic transport model, two approaches to model the gas network in detail have been proposed. On the one hand, the dynamic modeling represents in greater detail the operation of the gas network at the cost of significant computational complexity. On the other hand, steady-state modeling makes several simplifications to make the problem easier to solve. One of these simplifications is that the gas inflow to a pipeline is equal to its outflow. Therefore, the possibility of applying the linepack is not taken into account. The linepack is a way to provide flexibility to the gas network very appropriate for the short term, and that is why some authors have developed what is called quasi-static state modeling (Qadrdan et al., 2014; Zeng et al., 2017). This type of model uses a steady-state representation modified to consider an approximation of linepack. Equations (2.5) and (2.6) are maintained from the steady-state model, equation (2.7) is substituted by (2.8) to consider the possibility of having different gas inflows and outflows, and equation (2.9) is added to compute the gas stored by linepacking.

$$q_{n,m,t} = \frac{q^{in}_{n,m,t} + q^{out}_{n,m,t}}{2} \tag{2.8}$$

$$lp_{n,m,t} = lp_{n,m,t-1} + \left(q^{in}_{n,m,t-1} - q^{out}_{n,m,t-1}\right) \Delta t \tag{2.9}$$

where:

Δt time step

$lp_{n,m,t}$ linepack between nodes n and m at time t

2.3.2 Coordination strategies between gas and power systems

Tackling the problem of optimizing the power and gas systems can be done from four different approaches. The first two approaches focus on optimizing one of the systems, considering how the other can impact it. That is, optimize the power system incorporating constraints from the gas system that conditions its operation, or vice versa. For the last two, the idea is not to know how one system restricts the dispatching of the other but rather to optimize the operation of both together. This optimization can be done directly with both systems at the time or iteratively optimizing them and sharing information between executions till some degree of convergence.

2.3.2.1 Power system optimization with gas system constraints

This type of optimization focuses on the power system. The gas system is not represented in the same detail, but some aspects of it can be considered, including additional constraints. A typical example would be Security-Constrained Unit Commitment (SCUC) or robust optimization, where a possible congestion of the gas system have to be taken into account because they could lack supply to the Gas Fired Units (GFUs) (Alabdulwahab et al., 2015; T. Li et al., 2008; C. Liu et al., 2009; X. Zhang et al., 2016). In addition, impact on the gas price or price volatility can also be taken into account (Zhao et al., 2017).

2.3.2.2 Gas system optimization with power system constraints

In contrast to the previous one, this type of optimization focuses on the gas system with some consideration regarding the power sector. The use of CCGTs as base generation or as a complement to Renewable Energy Sources (RES), can cause significant changes in gas consumption. Therefore this type of optimization considers such impact when optimizing the operation of the gas system (Behrooz & Boozarjomehry, 2017; Chertkov et al., 2015; Hejazi & Mashhadi, 2016).

2.3.2.3 Sequential optimization of power and gas systems

The sequential execution consists of two separate problems that send instructions to each other (Clegg & Mancarella, 2015, 2016; Odetayo et al., 2017). Each problem aims to minimize operating costs while satisfying demand and is subject to interaction constraints with the other system. Generally, the power system is solved first, taking into account a gas cost. Subsequently, the gas system is solved accounting for the gas demand of the GFUs. If it is impossible to satisfy this gas demand, or if the costs associated with gas consumption vary significantly from those used in the first optimization, another iteration of both optimizations would be needed, sending the new instructions to the power system optimization. The sequential approach better reproduces what usually happens in real life where its most common to find independent SOs for each system and they do not share complete information among them. However, it is essential to keep in mind that this type of solution does not ensure the global optimality of the combined system as shown in (Qadrdan et al., 2014).

2.3.2.4 Joint optimization of power and gas systems

Joint optimization consists of taking into account the constraints of both systems simultaneously, whereas the objective function is to minimize the global cost (Correa-Posada & Sánchez-Martín, 2015a; J. Fang et al., 2018; He, Liu, et al., 2017a). Therefore, unlike sequential optimization, the simultaneous approach is able to guarantee optimal operation. The authors in (Ameli et al., 2017; Zlotnik et al., 2017) have shown such benefits by comparing both approaches. Simultaneous optimization usually requires a single operator to be in charge of both systems or, in the case of more than one, an extensive exchange of information between them. Having a single operator in charge of both systems is something that just a few countries have, like Denmark with Energinet. However, a joint optimization could establish a benchmark for the operation of the systems and evaluate their functioning even knowing that it is unattainable (Schwele et al., 2019). Furthermore, some studies propose decentralized algorithms to simulate the reality of information exchange while solving an optimization that seeks the optimum of the combined operation (He, Wu, et al., 2017; C. Liu et al., 2010; Wen et al., 2018).

The primary concern when solving the problem using the combined approach is its computational burden. Precisely because both systems are optimized at the same time, the problem becomes larger. Moreover, it is essential to keep in mind that in most solution methods, the cost of finding a solution does not grow linearly with the size of the problem. Hence, direct joint optimizations are much more complex to solve. For that matter, multi-level modelling or decomposition techniques can be implemented (Byeon & Van Hentenryck, 2020; G. Li et al., 2017; C. Liu et al., 2011).

2.3.3 Models using Third Party Access contracting explicitly

Section 2.3.2 Coordination strategies between gas and power systems presented how the problem of jointly optimizing power and gas systems can be addressed. From a joint system operation perspective, that is a good approach. However, from the perspective of an agent participating in the power market with a more economic point of view, the viability of the network operation (e.g., the power flow) may not be as relevant. Therefore, the approach that we apply is similar to that of Section 2.3.2.1 Power system optimization with gas system constraints, optimizing the power system with constraints of the gas system. As for those restrictions, they are not network constraints per se, but we consider the Third Party Access (TPA) fees that have to be paid to access the gas network, previously explained in Section 1.4 Third Party Access regulation.

Capacity contracting due to TPA tariffs is considered in the medium-long-term deterministic models as (Campos & Reneses, 2014; Dueñas et al., 2015). Authors in (Campos & Reneses, 2014) propose a deterministic price-based UC model (using Mixed Integer Linear Programming (MILP)) to optimize the generation and reserve operation of a Combined Cycle Power Plant (CCPP). They represent a single power plant considering every detail attending to the operation of the turbines, such as the Brayton and Rankine cycles, the minimum time and production levels to start-up the steam turbine, supplementary firing processes in the Heat Recovery Steam Generator (HRSG), or a fast-start mode. They use the model to study a whole year operation with fixed prices for electricity and gas, and daily and monthly TPA tariffs. In (Dueñas et al., 2015) the authors present a stochastic UC model (using MILP) to be used by a GenCo participating in an electricity market where a specific demand has to be covered. The GenCo buys gas in a spot market, acting as price-taker, and has to contract TPA capacity (annual, monthly, and daily options are considered). They study how a GenCo would make optimal long-term and medium-term decisions subject to short-term uncertainty using a system state representation (Wogrin et al., 2014). Still, the authors explicitly do not provide a model to guide short-term decisions.

2.3.4 Electricity and gas systems time synchronization

The measurement of time is a subject of great importance. The most widespread calendar in the western world is the Gregorian. However, although it is used as an international reference, this calendar is not the standard in all regions; for example, in China, they celebrate the beginning of the year according to the lunisolar calendar, and at the moment of writing this thesis, they are currently in the year 4720 (it started on 1 February 2022).

In energy systems, the time periods are also not the same in all areas. For example, in the electricity sector, it is common to use the concept of the *electricity week*, which is considered to start on Saturday and end on Friday. For electricity generation involving water usage, the hydrological year (also called water year, discharge year or flow year) is taken into account. It is start varies according to the geographical area due to the climate, being usual in the northern hemisphere to start between September and October. Regarding the gas system, the European Union has defined 31st October as the start of the gas year.

This thesis focuses on the short term, therefore it is not so relevant as to when years start. However, it is pertinent to take into account the daily synchronization. On the one hand, in the electricity system, the bulk of the energy is traded in the day-ahead market. Auctions are held every day where bids are submitted for the 24-hour of the following calendar day. In addition, on the next day, there are several intraday auction sessions where the trading horizon is until 24:00 of that day. On the other hand, in the gas system, the bulk of gas was traditionally traded by bilateral contracts, but now the spot markets are gaining relevance, as explained in Section 1.3.3 Gas acquisition. These markets use the *gas day* concept, which is a period of 24 hours (23h or 25h when there is a change from winter to summer time and vice versa) but not synchronized with calendar days.

Several authors have stated the importance of synchronizing both markets due to the inefficiencies that it can cause in the operation of GFUs (Wang et al., 2018; Weigand et al., 2013; Zhao et al., 2019). Furthermore, (Ji & Huang, 2017) shows the United States of America (USA) as an example where some participants of both markets have already declared to the Federal Energy Regulatory Commission (FERC) that market misalignment have affected their reliability and caused inefficiency. However, despite highlighting that the problem exists, the works reviewed use the assumption that the systems operate in a synchronized manner.

2.3.5 Other particularities of the Gas Fired Units

2.3.5.1 Operation and Maintenance

CCGTs can be seen as a perfect match for a renewable generation thanks to their flexibility in operation that allows them to cover for renewable generation uncertainty. While benefiting from those characteristics, these units experience more startups and shutdowns than standard thermal units. For that reason, special attention to the impact of their cycling operation cost should be taken into account in the short term. The most common operation and maintenance contracts are the so-called Long-Term Service Agreements (LTSA). Attention to the better modeling of short-term cost to incorporate in UC models the impact of the LTSA derived from the cycling operation has been given in studies such as (Hermans et al., 2018; Hermans & Delarue, 2017; Rodilla et al., 2014).

2.3.5.2 Turbine configurations

CCGTs are found with multiple configurations of gas and steam turbines (MxN) and can run in different modes. The most common design is one gas turbine paired with one steam turbine (1x1). Such configuration usually has no other implications as both turbines are used simultaneously. However, structures with more turbines, for example, two gas and one steam turbines (2x1, the second most common configuration), have two possible main operation modes. These modes would be to use the steam turbine with one or two gas turbines. While it is true that gas turbines could also be used without steam turbines, those operating modes are not commonly used beyond the start and stop maneuvers of the units. That is due to the high impact on efficiency that using the steam turbine has. However, switching from 1x1 to 2x1 modes has a less noticeable effect on efficiency, whereas it provides flexibility with a considerable increase in the power output. Therefore, those units are commonly used in different modes. Consequently, modeling all the possible modes of a 1x1 unit in detail is not as crucial as in units with a higher MxN configuration. In (Lu & Shahidehpour, 2004; Morales-España et al., 2016; Sun et al., 2018), different models considering MxN units are presented. Appendix B explains this subject in more detail and presents a formulation to represent the ability to change amongst different configurations by modeling the corresponding transitions with feasibility constraints and associated costs.

2.3.5.3 Weather conditions

It is not that common to consider environmental and weather variables while modeling the operation of thermal power units. However, units' performance is, in fact, affected by them. In (Geng et al., 2015), the authors studied how ambient temperature and pressure influence maximum power output and fuel consumption.

2.4 Strategic behavior

The regulatory conditions that GenCos face to optimize the scheduling of their power plants can be quite complex. 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 some aspects of real markets that have a profound impact on economic performance. In particular, we want to focus on two common problems faced by GenCos that can influence market results: the impact of electricity production, fossil fuel consumption, carbon emissions and market incomes taxation on the optimal operation of generation plants, and the impact of shared ownership of the generators.

The self-UC problem has been a fruitful research topic since the liberalization of the electric power industry took place. Given the diversity of possible market designs, when a GenCo faces the problem of planning the operation of its units, it is necessary to accommodate the specific market rules in the decision-making process. In addition, the impact of GenCo's actions on the resulting market prices might be relevant. When such influence is negligible, the GenCo can be considered as 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 can be taken into account leading to risk-neutral approaches where the expected profit is maximized, or to risk-based models where some risk-measure can be added to the optimization problem. 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 (Simoglou et al., 2010). However, for a price-maker, it is necessary to model explicitly the dependence of market prices on the output power.

This dependence can be modeled through residual demand curves (explained in detail in Section 2.4.1 Residual demand and income curves), which express the market price 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 authors in (Conejo et al., 2002) propose an iterative approach to solve the profit maximization of a GenCo using a simplified version of a residual demand curve (the *price–quota curve*), where several optimizations are performed until convergence is achieved. A more direct approach to overcome the non-linearity by building the corresponding income (or revenue) functions was firstly published in (García-González & Barquin, 2000), 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 MILP models to solve the strategic self-UC problem. In (de la Torre et al., 2002) the authors apply the same approach taking into account the detailed step-wise residual demand curves that can be built assuming a perfect knowledge about the offers and bids submitted by the rest of market participants. In (Cerisola et al., 2009) the authors use this approach to perform a self-UC for a whole week. In (Baíllo et al., 2001), 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 when the inherent uncertainty about the competitor's behavior must be taken into account to find the optimal offers, (Baíllo et al., 2004).

All those previous works require to introduce as input data the mentioned residual demand curves. Therefore, it is necessary to forecast the offers and bids of the other market participants, which can be a difficult task as it depends on the available historical data (Pelagatti, 2013; Soares et al., 2015). In particular, the presence of non-dispatchable renewable energy sources in the generation mix affects the shape of the offer curves dynamically, (Vázquez et al., 2014). In addition, if the market design is based on simple bids, the competitors' aggregated offer and bid curves can be used directly to build the residual demand functions. However, when complex bids are allowed (for instance, to declare an indivisible block to represent the minimum stable load of a thermal generator or minimum income conditions), the construction of hourly residual demand curves requires some additional processing as suggested in (Portela González et al., 2017).

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 which results in a bilevel problem. In (Bakirtzis et al., 2007), the resulting Mathematical Programming with Equilibrium Constraints (MPEC) is solved by formulating its equivalent MILP and by applying the binary-expansion method. The same approach is used in (Barroso et al., 2006), 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 (Kazempour & Hobbs, 2018a) and (Kazempour & Hobbs, 2018b) to consider the day-ahead and real-time markets and evaluate flexible resources.

2.4.1 Residual demand and income curves

In most day-ahead electricity markets, 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 $S(q^*) = D(q^*) = p^*$ as shown in

Figure 2.1.

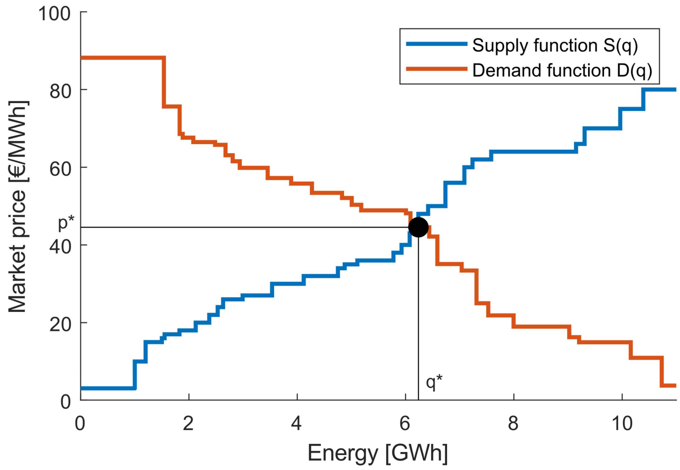


Figure 2.1: Electricity market clearing.

Given a specific 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, $R(q)$ express the market price p as a function of the total power produced and sold by the GenCo, i.e. $p = R(q)$ (García-González & Barquin, 2000; Portela González et al., 2017). An example of a residual demand curve for an hour is shown in Figure 2.2.

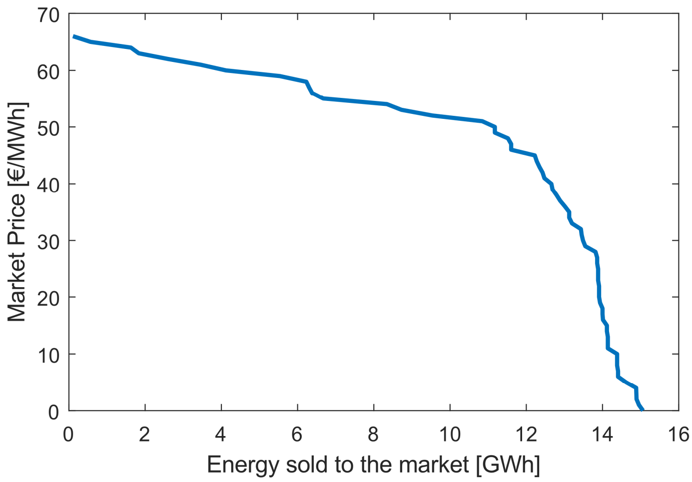


Figure 2.2: Residual demand curve (Iberian system H14 15/7/2013).

In order to maximize the profits, it is necessary to include the 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 period considered in the optimization. For that reason, the approach proposed in the literature consists in calculating this product ex-ante as an income curve and include 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 as a function to its energy sold to the market. 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 Figure 2.2 is displayed in blue in Figure 2.3. Notice that for null generation, the income is zero, although the market price cleared would be the maximum.

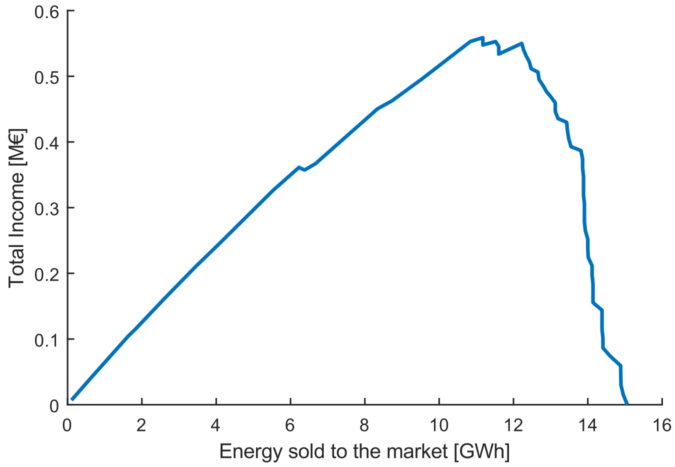


Figure 2.3: Income curve (Iberian system H14 15/7/2013).

The income curve can be modeled as a piece-wise linear function, and therefore, the resulting problem can be solved as a MILP optimization. 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. Figure 2.4 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 this example, the correspondences between the different sets are the following:

- According to $\Omega^{cs}_{w,t}$, the correspondences between the existing pairs of curve segments and concave sections (s, c) for hour t and scenario w are:

$$(s \in \{s1, s2\} \wedge c = c1) \rightarrow (s, c) \in \Omega^{cs}_{w,t}$$
$$(s \in \{s3, s4, s5, s6\} \wedge c = c2) \rightarrow (s, c) \in \Omega^{cs}_{w,t}$$

- According to $\Omega^{s}_{w,t}$ the existing segments s for hour t and scenario w are:

$$s \in \{s1, s2, s3, s4, s5, s6\} \rightarrow s \in \Omega^{s}_{w,t}$$

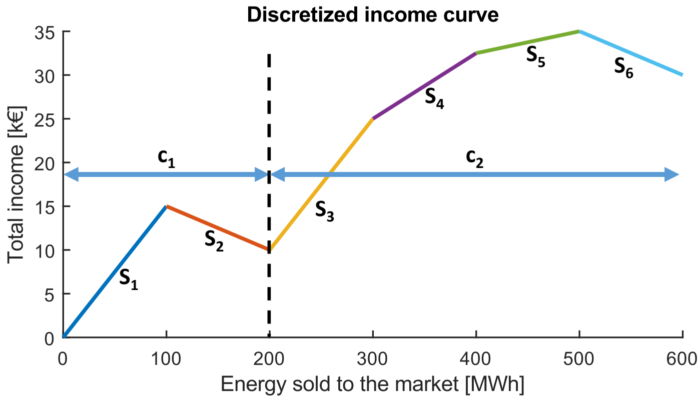


Figure 2.4: Illustrative income curve discretization example with segments s and concave intervals c.

2.4.2 Drawbacks of the formulation based on income functions

2.4.2.1 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 previously. 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 units are going to be cleared could be known beforehand, it could be possible to represent the correct income curve. However, if such sequence is not so easily predefined it is impossible to represent accurately the GenCos income.

For example, if we suppose a GenCo owning several units, of which the first three to be cleared (A, B, and C) have a maximum power output of 3GW; and regarding property, the GenCo owns 100% of all the units except for unit A, for which it only owns 50%. Figure 2.3 presents the three different curves that would result if unit A is cleared in first, second, or third place.

To analyze the implications of shared ownership of assets, let us use a simplified example in which there is a company that manages two generating units (G1 and G2), and due to the behavior of the rest of the system, the market price is 80€/MWh if the company does not produce any energy and falls at a rate of 0.1€/WMh.

Unit G1:

- Power: 200MW
- Ownership: 100%
- Generation cost: 20€/MWh

Unit G2:

- Power: 260MW
- Ownership: 50%
- Generation cost: 20€/MWh

Regarding the correct order in which the units should be committed, there is no such

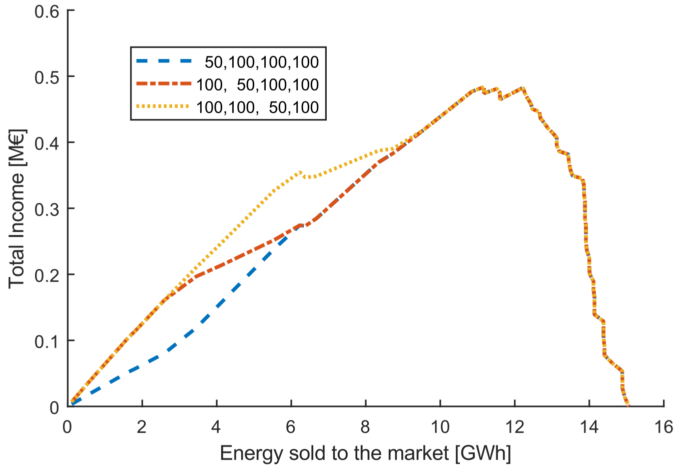
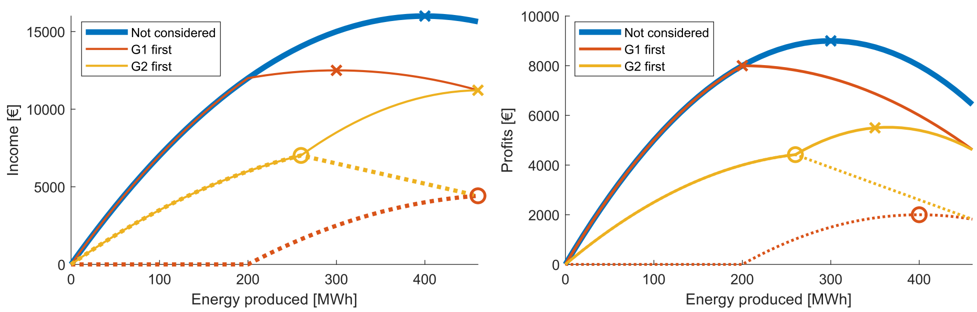


Figure 2.5: Income curve for different ownership and clearing orders (Iberian system H14 15/7/2013). The legend shows the units' ownership [%] in the expected order to be cleared.

order since both have a variable generation cost equal to 20€/MWh, and no additional terms such as a fixed cost or start-up cost are considered. Therefore, the only reason to use one instead of the other is the income obtained. Figure 2.6 shows the revenue (Figure 2.6a) and profit (Figure 2.6b) curves that would be obtained for three cases:

- The company owns 100% of both units.
- The company considers the actual ownership percentages and constructs its revenue curve assuming it commits G1 first and G2 second.
- The the the company considers the actual ownership percentages as in the previous case but committing G2 in the first place.



(a) Market income.

(b) Operation profits.

Figure 2.6: Income and profits for a case where shared ownership is not considered, and two where it is and the difference resides in the order in which units are committed. The continuous lines represent the company managing the assets whereas the company that just owns 50% of G2 is resented by the dashed lines. The maximums of each curve are marked with a cross for the managing company and with a circle for the other firm.

On the one hand, the first conclusion that can be drawn from these figures is that a company maximizing its profits will not behave in the same way if it owns the assets it manages, as if its units are shared with other agents. On the other hand, it is clear that depending on how the income curve is constructed according to a predefined merit order of the units, the operation will end up being different. Finally, it can also be seen that the interests of the different agents owning the units are opposed to each other; for each commitment sequence, one of the agents would be interested in generating less total energy while the other would prefer the opposite.

From the point of view of the whole system, another type of analysis would have to be carried out by confronting the system supply and demand curves to maximize social welfare. The supply curve would ignore the ownership of the units, and both G1 and G2 would be part of a single block represented by their variable cost of 20€/MWh. With the optimal solution obtained, if the energy to be produced by G1 + G2 is less than their maximum power, the allocation between the two units would affect the profits of the owning companies but not the system's social welfare.

2.4.2.2 Income tax

The income tax is a levy applied to market income itself. It is important not to confuse it with a more general tax applied to company's profits (total revenue minus total expenses). Such possible tax applied to company's results is out of this thesis's scope as it depends on the whole activity of the company and not just on the market-related operations.

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

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.

B) Two of the units have a tax of 4%, and the other (G1) has a tax of 6%. For this case, if the same approach is followed and the income curve is multiplied by 0.96, the results would underestimate G1's tax impact in 6-4=2% of its income. Approximations could be additionally applied to minimize the error's impact. For instance, one possibility would be to increase the cost of the generator by a factor related to the difference in the common tax applied to the income curve and the

G1's tax rate (factor = $(1 - TxC)/(1 - TxI_g)$). To better illustrate this example, let's analyze its results:

- Tax of unit G1 = 0.06 p.u.
- Tax applied to the income curve = 0.04 p.u.
- Market price = 70€/MWh
- Income tax of unit G1: $TotalTax = Price \cdot TxI_g = 70 \cdot 0.06 = 4.2$ €/MWh

The income curve is modified to account for a reduced price: $ReducedPrice = Price(1 - TxC) = 70(1 - 0.04) = 67.2$€/MWh. Therefore, the income tax already accounted in the income curve is 2.8€/MWh, and the cost of the unit has to be increased to approximate the difference with the $TotalTax = 4.2$€/MWh. To account for such difference with the common tax expense, equation (2.10) is used. Table 2.2 shows how the approximation would perform in case the unit has a cost that makes it an infra-marginal, marginal or supra-marginal generator in the market.

$$IncreasedCost_g = \frac{RealCost}{\frac{1-TxI_g}{1-TxC}} \tag{2.10}$$

Table 2.2: Tax approximation depending on whether the unit is infra-marginal, marginal, or supra-marginal. All units are expressed in [€/MWh].

Possible cases	Infra-marginal unit	Marginal unit	Supra-marginal unit
Real cost	60.000	65.800	70.000
Increased cost	$\frac{60.0}{\frac{1-0.06}{1-0.04}} = 61.276$	$\frac{65.8}{\frac{1-0.06}{1-0.04}} = 67.200$	$\frac{70.0}{\frac{1-0.06}{1-0.04}} = 71.489$
Tax by increasing cost	1.275	1.400	1.489
Total tax considered	4.076	4.200	4.289
Difference with total	-0.124	0.000	0.089

The income tax of the market marginal unit is correctly calculated by approximating such levy by artificially increasing the generation cost of the unit. For those units that are infra-marginal or supra-marginal, the income tax is underestimated and overestimated, respectively. Given an ideal situation where the generation units could be characterized only by a variable cost, this approximation would be enough for a centralized optimization. The reason is that the error incurred by the approximation would never imply an alteration in the order in which the units are cleared, and the calculations are exact for the marginal unit. However, from a profit maximization perspective, where the price impact is considered, it is also crucial to characterize the taxes of the inframarginal units correctly. When the optimizer analyzes the profit of generating an additional MWh, it calculates the revenue that additional MWh will bring against the income that the rest of the generation stops earning due to the price decrease. If the taxes of these units are not correctly modeled, the calculation of the foregone revenue is not correct.

This approximation does not intend to solve the problem as such but rather improve the state-of-the-art formulation that in Chapter 4 will serve as a benchmark for the comparison with the formulation proposed in this thesis. In the proposed formulation, the income tax will be accurately modeled and will not need to be approximated.

Section 1.5.1 The Spanish case explained the different taxes applied in Spain, where various taxes are applied to different technologies and geographical areas. Therefore, this problem regarding the existence of units with different taxes is present.

2.5 The Unit Commitment problem

The UC problem is one of the most critical problems in power systems operation. Its purpose is to determine the optimal commitment status of the power generation units. However, it is a non-trivial problem due to the size of real systems and the computational limitations. For this reason, it is one of the problems that most interest arouses and that has been extensively studied over the years. Without going any further, it is not difficult to find several reviews of the state of the art focused on this problem just in the last two years (Hong & Apolinario, 2021; Kumar et al., 2021; Montero et al., 2022; N. Yang et al., 2021).

Traditionally, the UC problem has been studied as the minimization of costs while satisfying the demand, which is a centralized management approach. However, it is increasingly common not to use this approach nowadays because there has been a gradual liberalization of the markets. The objective of an individual agent participating in the market is not to minimize the costs because there is no associated demand for any specific player. Still, there is a market in which the agent participates, and therefore the objective of the UC problem is to maximize the profits (García-González & Barquin, 2000). Theoretically, in a competitive environment without dominant players, profit maximization by the different agents also minimizes system costs. The approach adopted in this thesis is more oriented to the second one, an individual agent seeking to maximize its profits in the market.

To achieve an optimal solution, several methodologies have been proposed over the years: exhaustive enumerations (Hara et al., 1966), expert systems (S. Li et al., 1993), priority listing (Shahbazitabar & Abdi, 2018), fuzzy logic (N. Zhang et al., 2015), machine learning (Y. Yang & Wu, 2021), optimization problems, or hybrid methods combining some of the previous (Patra et al., 2009). For the optimization problem, there are two possible approaches. On the one hand, the conventional optimization (Morales-España et al., 2013) formulates the problem as an objective function subject to some constraints. On the other hand, the dynamic programming (Zou et al., 2019) is based on the Bellman's optimality principle (Bellman, 1957). Regarding the formulation of the problem, the variables can be discrete or continuous, and the equations can be linear, quadratic, or nonlinear. According to (Montero et al., 2022), in the UC problem, the most used methodology is the conventional optimization problem, and for its formulation, the most popular is the MILP formulation that uses both integer and continuous variables with linear equations. On the one hand, the main disadvantages of this methodology are: the need for simplifications, such as function linearizations, and its exponential increase in computational load as the problem size increases. On the other hand, its main advantages are: its wide use in the literature, the ease of implementation, the guarantee of obtaining a global optimal solution (even if an optimality gap has to be applied to shorten the solution time), and the availability of powerful commercial solvers such as Gurobi[1] or CPLEX[2]. In (Tejada-Arango et al., 2020) the authors compare the three current state-of-the-art MILP formulations: tight and compact (Morales-España et al., 2013), state transition (Atakan et al., 2018), and projected two-binary-variable (L. Yang et al., 2017). Their results determine that the tight and compact formulation generally performs better regarding integrality gap and CPU time.

This thesis focuses on improving the management of CCGTs in real settings; for that reason, as the MILP is the most widely used, it has been the chosen formulation. A descriptive example of this type of formulation from an agent's perspective is presented below. As this thesis is focused on electricity generation using thermal units, no hydro generation is included in the formulation for clarity.

$$\max \left(MarketIncome - GenerationCost - Taxes \right) \tag{2.11}$$

Subject to income, cost and taxes calculation:

- Market income: use fixed electricity prices or model impact in market prices.
- Generation cost:
  - Operation and Maintenance (O&M): cost associated with the number of hours functioning and start-up maneuvers.
  - Fuel: the consumption is calculated according to power output and start-up and shut-down maneuvers. The cost depends on fuel acquisition (fixed price or impact in market price) and TPA tariffs.
- Taxes:
  - Fuel consumption.
  - Power generation.
  - Market income.
  - CO_2 emissions.

and technical constraints:

- Power limits: operation between maximum and minimum power output.
- Ramping limits: maximum variation in power output.
- Min time on/off: minimum time the units have to be on/off after a start-up/shut-down decision.

[1]Gurobi optimizer: https://www.gurobi.com/
[2]CPLEX optimizer: https://www.ibm.com/es-es/analytics/cplex-optimizer

- Start-up type: type of start-up decisions according to the time the units have been down.
- Commitment coherence: relation between commitment status and start-up and shut-down decisions.
- Consumption: constraints regarding fuel consumption.

2.5.1 Uncertainty consideration

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 (van Ackooij et al., 2018) for a specific review of these techniques).

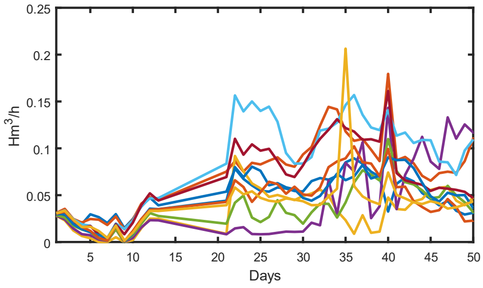
2.5.1.1 Stochastic optimization

Stochastic optimization (Håberg, 2019) uses a series of scenarios with an assumed known probability of occurrence. These scenarios must be selected so that they represent the uncertainty in the best possible way. This is precisely the weak point of this technique: on the one hand, it is challenging to identify such probability distributions, and on the other hand, it requires a large number of scenarios to cover the whole uncertainty spectrum.

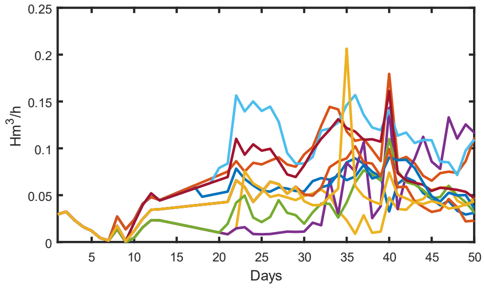
In stochastic optimization, the objective function minimizes (maximizes) the expected value of the operating cost (profit), which is the result of multiplying the value of this variable in each scenario by the probability of occurrence of the corresponding scenario. Generally, stochastic modeling is done in two steps, where there are first-stage variables common to all scenarios and second-stage variables that depend on each scenario. For example, when scheduling the operation of the generators for the day-ahead market, it is usual to consider the commitment state as a first-stage variable. In contrast, the power output in each hour is a second-stage variable. Four solutions methods are presented in (Cerisola et al., 2009) for optimizing the UC of a whole week using a multistage stochastic setting. Stochastic optimization for coordination of gas and power systems can be found in (Alabdulwahab et al., 2017; Kanelakis et al., 2020; Shabazbegian et al., 2020)

As already mentioned, the uncertainty increases as the predicted period moves away from the time of prediction, so it is common to present the scenarios in the form of a tree. That tree starts with a common branch, and as the time horizon progresses, it divides into other branches. Its main advantage over considering a fixed number of scenarios from beginning to end is its better computational burden, due to the reduction of possibilities. In Figure 2.7 an example with the two options is presented for the water inflows on a reservoir during a period of 50 days. Figure 2.7a and Figure 2.7c are the data and scenario structure for the ten independent scenarios, and Figure 2.7b and

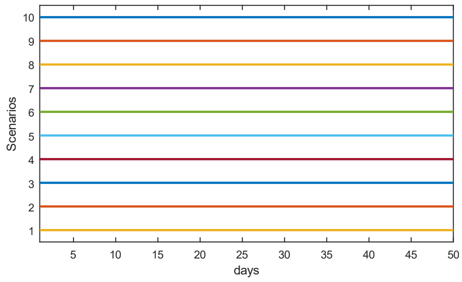
Figure 2.7d are the corresponding data and structure when the tree representation is used.



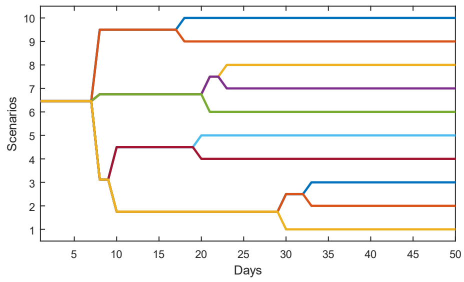
(a) Data for independent scenarios.



(b) Data in tree structure.



(c) Independent scenarios.



(d) Scenario tree structure.

Figure 2.7: Water inflow scenarios at a reservoir.

In this thesis, scenario reduction and tree construction processes have been applied with the techniques presented in (Dupačová et al., 2003; Heitsch & Römisch, 2003). Such implementation has been done in General Algebraic Modeling Language (GAMS) using the ScenRed2[3] tool. That tool requires just a few configuration parameters such as to whether to reduce the number of scenarios or build a tree, the number of final scenarios and the periods when bifurcations may occur. In addition, ScenRed2 allows using two opposite strategies: *forward* and *backward*. The *forward* strategy starts from nothing and iteratively selects the most representative scenario until the desired number of scenarios is obtained. In contrast, the *backward* strategy begins with all the original scenarios and iteratively eliminates the least representative till the desired amount is reached. For that reason, the type of algorithm to be used depends on the number of original vs. selected scenarios.

2.5.1.2 Robust optimization

The main idea of robust optimization is to provide suitable solutions for the worst-case scenarios that may result from the combinations of variables with uncertainty. Instead of using probability distributions, bounded ranges are used for the uncertain variables. The conservativeness of the robust solution can be controlled with an uncertainty budget. Its main advantage over stochastic optimization is its lower computational burden and the fact that it does not need as much information about uncertain variables. However, it

[3] ScenRed2 software: https://www.gams.com/38/docs/T_SCENRED2.html

may result in overly cautious solutions, and also difficult techniques may be necessary to implement a *min-max-min* scheme. Such structure consist of minimizing the maximum value of the objective function obtained for the different scenarios when minimizing the operation cost. Authors in (Morales-España et al., 2018) propose a UC robust optimization for dealing with wind uncertainty, whereas (He, Liu, et al., 2017b) also tackles the wind uncertainty optimizing the coordinated operation of gas and power systems.

This type of optimization makes a lot of sense from the point of view of a SO, for whom the security of the network must be guaranteed, and therefore it must be protected against worst-case scenarios. From the point of view of a profit-maximizing agent, the worst-case scenario would be related, for example, to worst-case prices, and robust optimization could prevent money losses. However, the over-caution approach of robust optimization makes stochastic optimization more profitable in the long run.

2.5.1.3 Chance-constrained optimization

It is an optimization technique that deals with uncertainty, focusing on the model constraints (van Ackooij et al., 2011; Y. Zhang et al., 2017). This formulation aims to reduce the number of times that specific constraints are violated for a particular solution to the problem for the different scenarios. According to (van Ackooij et al., 2018) this is the least used technique in the UC problem.

2.5.1.4 Hybrid approaches

Some authors also use this hybrid approach combing stochastic and robust optimizations as distributionally robust optimization. This technique tries to minimize their drawbacks: the stochastic approach probability inaccuracy, and the over-conservatism of the robust approach. For this purpose, it defines an ambiguity set consisting of a family of possible distributions and keeps the robust idea of protecting against the worst-case scenario. Regarding the UC problem, (Xiong et al., 2017) considers wind uncertainty, and in the integrated optimization of gas and power systems (He et al., 2019) deal with gas and electricity demand respectively. In (X. Fang et al., 2019) considers uncertainty in wind generation using distributionally robust chance-constrained optimization.

2.6 Conclusions

The main objective of this thesis is to improve the short-term hourly scheduling model from the point of view of a GenCo participating in the power market, i.e., the so-called self-UC problem. Among all the assets that such a company may have, we will focus on the CCGTs.

The first issue to consider is the type of modeling we are going to implement. As mentioned before, the MILP formulation using commercial solvers is the most powerful and widespread, and specifically, the tight and compact formulation is the most efficient. Therefore, we have chosen this formulation as the base to improve it.

The second issue has to do with the type of units we have decided to focus on, the CCGTs. This generation units consume gas delivered through a network, complicating their operation. As we have seen, modeling the gas network itself is not trivial. Numerous studies address the best way to model the gas network in greater or lesser detail and consider its interaction with the power system to a greater or lesser extent. However, from the point of view of the individual agent, these dynamics of the network detailed modeling are not so relevant, being much more interesting to focus on the economic implications they have, i.e., the cost structure derived from using the gas network. It is in this cost structure where TPA tariffs comes into play. They are fees that have to be paid for using the gas system. In this respect, we have started by reviewing the situation in the European Union (EU) at the regulatory level. In addition, we have found that it is not common to consider such tariffs in the cost calculations, and we have not found them applied in short-term self-UC models. TPA tariffs are particularly important because they 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. These issues are neglected in all the previous works that consider as input data the cost functions of each generation unit in an individual manner.

Thirdly we will try to solve the issues that arise with generation unit shared ownership and taxation. 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 thesis 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. Particular attention should be paid to the last one because it can be very challenging when formulating the profit maximization problem for a price-maker participant. All the review works express the incomes of the GenCo through an aggregated portfolio approach. Therefore when there is a tax that depends on the market income of a particular generator, such a portfolio approach cannot consider separate charges for each power plant. In addition, when the ownership percentage of a generator is not 100%, the portfolio approach can neither represent the income of such generator appropriately as the market-clearing for each possible market price is uncertain.

Finally, we pay attention to GenCos that may be dominant players. Companies are not allowed to exercise market power, but that does not automatically eliminate the theoretical influence that their actions could have on market results. Therefore, they must take this consideration into account and respect the rules while planning the operation of their units. From the system's perspective, models that maximize social welfare are proposed. However, from an agent's perspective, the models are aimed at profit maximization. In addition, it is essential to take into account the available information. For example, to model a market equilibrium, it is necessary to know in some way the information about the competing generation units. In contrast, a profit optimization based on residual demand curves only uses public data regarding the competing offers sent to the market. Therefore, profit optimization makes sense, but it can lead to solutions that exert market power. On paper, they are suitable for theoretical studies, but in the real world, they must be avoided.

Chapter 3

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

The developments presented in this chapter are reflected in two publications, a simplified deterministic version *"Impact of Gas Third Party Access in the Unit Commitment Optimal Solution"*, presented in 2019 Institute of Electrical and Electronics Engineers (IEEE) Milan PowerTech (Otaola-Arca et al., 2019), and the complete stochastic version *"Modeling of Third Party Access Tariffs and Portfolio Gas Purchases of CCGTs in the Self-Unit Commitment Problem"* published in IEEE Transactions on Power Systems on 25 November 2020 (Otaola-Arca et al., 2021).

3.1 Introduction

Gas Fired Units (GFUs), such as Combined Cycle Gas Turbines (CCGTs), are expected to play an essential role in the decarbonization process of the electricity sector during the following years. They are used to produce energy in the power system and are also connected to the gas system, from where they extract the fuel they need to operate. It is important to highlight that the gas sector is a network industry that requires an adequate tariff design to recover the cost of building, running, and maintaining the infrastructure, as explained in Section 1.3.2 Gas sector general description. From the regulatory point of view, we focus on the systems that have implemented a Third Party Access (TPA) tariff design. 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 (Mehr et al., 2013). In Section 1.4 Third Party Access regulation the European regulation has been detailed, and that is precisely the framework we are going to tackle in this chapter.

With this TPA framework, Generation Companies (GenCos) face the problem of finding the optimal scheduling of their 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 they contract (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.

In this chapter, we provide a detailed mathematical formulation of the stochastic self Unit Commitment (self-UC) model, including the TPA tariffs and portfolio gas purchases for different settings. We perform a comparison with the standard formulation to highlight the importance of considering TPA and joint gas purchases in the gas spot market on the self-UC problem. In addition, our proposed models can be used by GenCos to determine the TPA quantities (monthly and daily) that they should contract. In contrast, in the case of using the traditional formulation, such amounts would have to be determined by a specific tool after the optimization process.

The remainder of this chapter is organized as follows:

- Section 3.2 Considerations for Generation Companies describes the actual problem faced by a GenCo in charge of operating some CCGTs.
- Section 3.4 Mathematical formulation presents the traditional and proposed formulations, explaining in detail how they work.
- Section 3.5 Case Study displays a study case where formulations are compared to state the relevance of the proposed approach.
- Section 3.6 Conclusions summarizes the main conclusions.

3.2 Considerations for Generation Companies

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:

- The GenCo has to find the optimal TPA contracting strategy and include its related cost in the optimization.
- There is a time offset between TPA products and electricity day-ahead market.
- TPA services have monthly and daily periods and therefore at least a whole month must be simulated.

- TPA tariffs are deterministic input data parameters.

- 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 Figure 3.1. Notice that the end of the month is slightly displaced due to the mentioned time offset that affects gas products (Section 2.3.4 Electricity and gas systems time synchronization). 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 GenCo 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, Figure 3.1 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 GenCo is at the end of week 1 in Figure 3.1. 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 Figure 3.1, the first two days of the optimization horizon belong to month 1, and therefore, their corresponding monthly TPA are input parameters.

We propose a multistage stochastic optimization approach, 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. However, when facing uncertain outcomes, it is necessary to consider the level of risk aversion of the decision maker. The proposed modeling is formulated as a risk-neutral problem. In case that it may be 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 (Rockafellar & S.Uryasev, 2000), and to define the Unit Commitment (UC) objective function as the mean-risk problem (Jo-

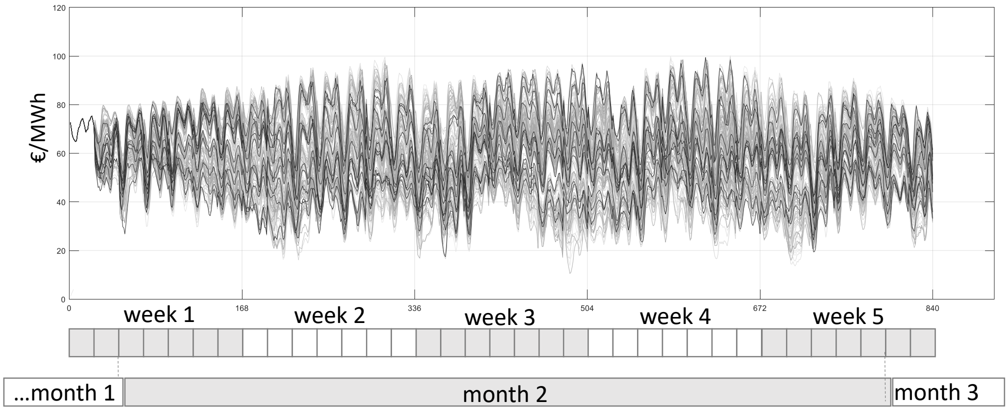


Figure 3.1: Electricity price scenarios (darker color corresponds to a higher probability of occurrence).

vanovic et al., 2017), i.e. a weighted sum of the mean value and the CVaR that allows to model different levels of risk aversion.

3.3 Methodology

The main aim of this chapter is to highlight the importance of considering TPA contracting in the self-UC scheduling optimization. In addition, the possibility that exists to make use of the storage infrastructure to increase the profits by performing arbitrage between markets is also presented.

A complete formulation able to deal with all possibilities is presented. However, to develop the explanation and keep the focus on the different matters, several models have been defined in Section 3.4.5 Model definitions. These models are the standard formulation and the three versions of the proposed one that use part of the constraints.

On the one hand, a model comparison between the proposed formulation, ignoring the storage options, and the standard one, where the cost parameters try to include the TPA-related cost, is performed to highlight the importance of correctly modeling the TPA tariffs. This comparison uses one formulation that models some costs in detail (the proposed one) and another (the standard one) that considers such costs through some kind of estimation by increasing the generation cost parameters of the generation units. It is important to note that in order to make this comparison fair, the best possible estimation of these parameters has been calculated (the calculation methodology is detailed in the example case). Therefore this comparison establishes a lower limit to the improvement of the solution that can be obtained by using the proposed formulation. On the other hand, a second comparison between the proposed formulation that uses the storage, with and without allowing to sell gas to the market is presented to show how a GenCo can profit from arbitrage between markets.

3.4 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. The main model is formulated as a multistage stochastic Mixed Integer Linear Programming (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 (Cerisola et al., 2009), Danzig-Wolfe decomposition (Schulze et al., 2017), Progressive Hedging (Gade et al., 2016), and stochastic dual dynamic integer programming (Zou et al., 2019). In addition, the search procedure could be improved by applying the branch-and-fix coordination algorithm (Aldasoro et al., 2017). The stochastic modeling approach has been presented in in Section 2.5.1.1 Stochastic optimization, and its formulation is detailed in Appendix A.2 Uncertainty formulation.

3.4.1 Assumptions

Energy deregulation varies by country and the liberalization process for the electricity and gas sectors can have different development speeds. We assume 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 chapter, 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. Considerations regarding price-maker agents are in Chapter 4 Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology.

- 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.

3.4.2 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. are presented in Appendix A.3 Unit Commitment technical constraints and are not duplicated here for the sake of simplicity. Regarding the stochastic formulation, the implementation of the tree-structured scenarios is detailed in Appendix A.2 Uncertainty formulation.

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 $csTot_w$ considering the probability of each scenario, (3.1):

$$\max \left(\sum_{w \in W} Prob_w \left[\sum_{\substack{t \in T \\ w' \in \Omega_{w,t}^{w'}}} \left[\mathit{\Pi}_{w',t}^{E} \sum_{g \in G} [pt_{w',g,t}] \right] - csTot_w \right] \right) \tag{3.1}$$

In the standard self-UC formulation, the cost $csTot_w$ is computed by adding the individual cost functions of each generator as in (3.2):

$$\begin{aligned} csTot_w = & \sum_{\substack{g \in G \\ t \in T \\ w' \in \Omega_{w,t}^{w'}}} [CSmn_g \cdot v_{w',g,t} + CSvr_g \cdot p_{w',g,t} + CSsd_g \cdot z_{w',g,t}] \\ & + \sum_{\substack{g \in G \\ t \in T \\ w' \in \Omega_{w,t}^{w'} \\ su \in SU}} [\delta_{w',g,t,su} \cdot CSsu_{g,su}] \qquad \forall w \in W \end{aligned} \tag{3.2}$$

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 (3.2) by (3.3)-(3.13). 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, and therefore, sets Ω_d^t and Ω_{dg}^t are not equivalent (the same applies to gas months).

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

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

For the gas acquisition, every gas day dg and scenario w is characterized by a given gas price $\mathit{\Pi}^{G}_{w,dg}$. The amount of gas bought each day is represented by variable $qb_{w,dg}$ that depends only on the day and scenario w.

Equation (3.3) presents the total generation cost including: TPA ($csT_{w,x,mg}$), storage ($csS_{w,x,mg}$), gas supply ($csSup_{w,dg}$), Operation and Maintenance (O&M) ($csOM_{w,g,t}$), and CO_2 emissions cost ($csCO2_{w,g,t}$). These five terms are computed in (3.4), (3.5), (3.6), (3.7), and (3.8) respectively.

$$\begin{aligned} csTot_w = & \sum_{\substack{x\in X \\ mg\in MG \\ w'\in\Omega^{w'}_{w,mg}}} [csT_{w',x,mg} + csS_{w',x,mg}] + \sum_{\substack{dg\in DG \\ w'\in\Omega^{w'}_{w,dg}}} [csSup_{w',dg}] \\ & + \sum_{\substack{g\in G \\ t\in T \\ w'\in\Omega^{w'}_{w,t}}} [csOM_{w',g,t} + csCO2_{w',g,t}] \qquad \forall w \in W \end{aligned} \tag{3.3}$$

TPA contracting cost at each power plant exit point (3.4) depends on the amount of daily and monthly capacity contracted and gas usage.

$$\begin{aligned} csT_{w,x,mg} = mT_{w,x,mg} \cdot Tm_{x,mg} + \sum_{\substack{dg\in\Omega^{dg}_{mg} \\ w'\in\Omega^{w'}_{w,dg}}} [cnX_{w',x,dg} \cdot Tu_{x,mg} + dT_{w',x,dg} \cdot Td_{x,mg}] \\ \forall w \in \Omega^{w}_{mg}, x \in X, mg \in MG \end{aligned} \tag{3.4}$$

Storage cost (3.5) depends on capacity contracted at storage facilities plus injections and extractions to/from the facilities.

$$csS_{w,x,mg} = \sum_{\substack{dg \in \Omega^{dg}_{mg} \\ w' \in \Omega^{w'}_{w,dg}}} [dS_{w',x,dg} \cdot Sd_{x,mg} + iS_{w',x,dg} \cdot Si_{x,mg} + eS_{w',x,dg} \cdot Se_{x,mg}]$$
$$+ mS_{x,mg} \cdot Sm_{x,mg} \qquad \forall w \in \Omega^{w}_{mg}, x \in X, mg \in MG \tag{3.5}$$

Gas supply cost (3.6) represents the cost of gas purchases.

$$csSup_{w,dg} = \mathit{\Pi}^{G}_{w,dg} \cdot qb_{w,dg} \qquad \forall w \in \Omega^{w}_{dg}, dg \in DG \tag{3.6}$$

The O&M cost of each generator (3.7) considers a fixed charge per start-up maneuver and a fixed term per hour being committed.

$$csOM_{w,g,t} = OMsu_g \cdot y_{w,g,t} + OMh_g \cdot v_{w,g,t} \qquad \forall w \in \Omega^{w}_{t}, g \in G, t \in T \tag{3.7}$$

CO_2 cost (3.8) is expressed in terms of the gas consumption, the gas to CO_2 ratio, and CO_2 emissions price.

$$csCO2_{w,g,t} = cnG_{w,g,t} \cdot CO2r_g \cdot PCO2 \qquad \forall w \in \Omega^{w}_{t}, g \in G, t \in T \tag{3.8}$$

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

Gas consumption at each exit point (3.10) 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 (3.9) are calculated as a gas-to-power expression and the gas consumption of each start-up and shut-down maneuver.

$$\begin{aligned} cnG_{w,g,t} =& CNmn_g \cdot v_{w,g,t} + CNvr_g \cdot p_{w,g,t} \\ &+ \sum_{su \in SU} [CNsu_{g,su} \cdot \delta_{w,g,t,su}] + CNsd_g \cdot z_{w,g,t} \qquad \forall w \in \Omega^{w}_{t}, g \in G, t \in T \end{aligned} \tag{3.9}$$

$$cnX_{w,x,dg} = \sum_{\substack{g \in G \\ t \in \Omega^{t}_{dg} \\ w' \in \Omega^{w'}_{w,t}}} [cnG_{w',g,t}] \qquad \forall w \in \Omega^{w}_{dg}, x \in X, dg \in DG \tag{3.10}$$

TPA capacity contracting (3.11) must account for the exit point gas consumption to ensure that the total contracted capacity (computed as the sum of the daily, monthly and pre-contracted terms) is respected by the obtained scheduling:

$$cnX_{w',x,dg} \leq dT_{w',x,dg} + Tp_{x,dg} + mT_{w,x,mg}$$
$$\forall w \in \Omega^{w}_{mg}, w' \in \Omega^{w'}_{w,dg}, x \in X, dg \in \Omega^{dg}_{mg}, mg \in MG \tag{3.11}$$

The daily/monthly storage capacity (3.12) that has to be contracted depends on the gas stored (available gas $qa_{w,dg}$). Gas injections/extractions to/from storage facilities (3.13) depend on used and bought gas.

$$qa_{w',dg} \leq \sum_{x \in X} [dS_{w',x,dg} + mS_{x,mg} + Sp_{x,dg}]$$
$$\forall w \in \Omega^{w}_{mg}, w' \in \Omega^{w'}_{w,dg}, dg \in \Omega^{dg}_{mg}, mg \in MG \tag{3.12}$$

$$qb_{w,dg} = \sum_{x \in X} [cnX_{w,x,dg} + iS_{w,x,dg} - eS_{w,x,dg}]$$
$$\forall w \in \Omega^{w}_{dg}, dg \in DG \tag{3.13}$$

Gas available for a certain day (3.14) depends on the previous day available gas, plus purchases minus consumption of the total portfolio. The gas available for the first simulation day (3.15) is input data to the model.

$$qa_{w,dg} = qa_{w',dg-1} - \sum_{x \in X} [cnX_{w',x,dg-1}] + qb_{w',dg-1}$$
$$\forall w \in \Omega^{w}_{dg}, w' \in \Omega^{w'}_{w,dg-1}, dg \in DG - \{1\} \tag{3.14}$$

$$qa_{w,dg} = Avail$$
$$\forall w \in \Omega^{w}_{dg}, dg \in \{1\} \tag{3.15}$$

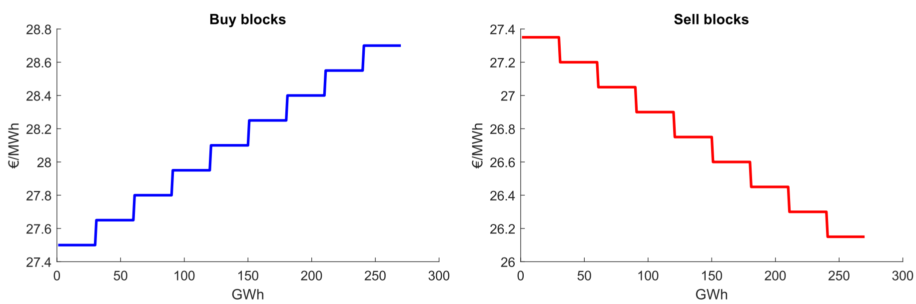
3.4.3 Modeling the possibility of affecting the price in the gas market

As previously stated in Section 1.3.3 Gas acquisition, there are mainly two alternatives for gas procurement: bilateral contracts with generators (with fixed or indexed prices) or purchases in gas spot markets.

When handling large gas volumes, there is undoubtedly some impact on the gas prices. In this thesis, we have assumed that the larger the purchased quantity, the higher the cost (vice versa for sales). This was the approach followed in (Gil et al., 2013) and it has been used in this thesis to represent the change in the gas price as a function of the total quantity of gas purchased or sold. In particular, this function has been modeled by monotonically increasing/decreasing steps in which each extra block of gas has a higher price when buying and a lower price when selling. This modeling can represent two different realities. On the one hand, bilateral contracts where each block is a pay-as-bid offer and therefore, the larger the amount of gas, the higher the price the GenCo has to pay to its supplier for it. In the case the GenCo wanted to sell the gas, the price has to be lower for each additional block of gas to be sold. These two possibilities are displayed in Figure 3.2 where the blue step-wise function represents the purchase blocks and the red one the sell blocks.

On the other hand, besides these bilateral contracts signed by the company to procure its gas, it might also be possible to trade gas in a spot market. In case this spot market is marginalist, the agent could build its residual supply curve that relates the resulting market price with the whole daily quantity bought in the market. This is represented by the blue curve in Figure 3.3. If the GenCo wanted to sell its gas, the red curve in Figure 3.3 represents the residual demand curve of the gas market. In this case, as in (Gil et al., 2013), it is supposed that the curves in Figure 3.2 are monotonic. This modeling approach is valid for a relatively small price impact since it is not intended to consider agents with market power and analyze its possible implications. In fact, if the price impact was more significant, additional considerations would have to be made, as not all the residual demand curves can always be represented by equivalent pay-as-bid monotonic decreasing step functions.

In a real setting where there is a spot market, a GenCo uses a combination of bilateral contracts and market purchases. Therefore, the common practice is that the GenCo's corresponding gas department is responsible for building the functions in Figure 3.2 trying to represent as accurately as possible the actual actual GenCo's options. For this model, the following equations (3.16)-(3.20) must replace equations (3.6),(3.13), and (3.14), and the variable representing the purchased gas depends on the indexes day, scenario, and block ($qb_{w,dg,b}$).



(a) Blocks available to buy. (b) Blocks available to sell.

Figure 3.2: Gas market price impact example.

Gas supply cost (3.16) represents the cost of gas purchases minus the income of gas sales.

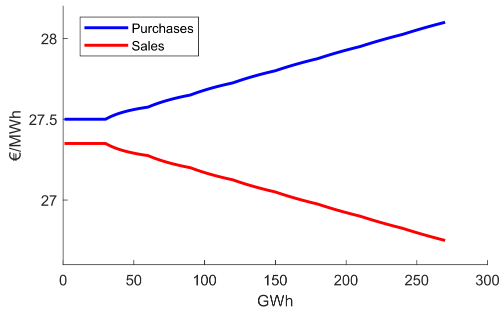


Figure 3.3: Equivalent residual demand/supply curves for the gas market price impact example.

$$csSup_{w,dg} = \sum_{b \in B} [qb_{w,dg,b} \cdot Pb_{w,dg,b} - qs_{w,dg,b} \cdot Ps_{w,dg,b}] \qquad \forall w \in \Omega^{w}_{dg}, dg \in DG \tag{3.16}$$

Gas injections/extractions to/from storage facilities (3.17) depend on used and traded gas.

$$\sum_{b \in B} [qb_{w,dg,b} - qs_{w,dg,b}] = \sum_{x \in X} [cnX_{w,x,dg} + iS_{w,x,dg} - eS_{w,x,dg}] \qquad \forall w \in \Omega^{w}_{dg}, dg \in DG \tag{3.17}$$

Purchases (3.18) and sales (3.19) are limited to the quantities available in each step of the functions that define the gas prices.

$$qb_{w,dg,b} \leq Qb_{w,dg,b} \qquad \forall w \in \Omega^{w}_{dg}, dg \in DG, b \in B \tag{3.18}$$

$$qs_{w,dg,b} \leq Qs_{w,dg,b} \qquad \forall w \in \Omega^{w}_{dg}, dg \in DG, b \in B \tag{3.19}$$

Gas available for a certain day (3.20) depends on the previous day available gas, plus purchases, minus sales, minus consumption of the total portfolio.

$$qa_{w,dg} = qa_{w',dg-1} - \sum_{x \in X} [cnX_{w',x,dg-1}] + \sum_{b \in B} [qb_{w',dg-1,b} - qs_{w',dg-1,b}]$$
$$\forall w \in \Omega^{w}_{dg}, w' \in \Omega^{w'}_{w,dg-1}, dg \in DG - \{1\} \quad (3.20)$$

3.4.4 Stochastic particularities

As explained in Appendix A.2 Uncertainty formulation, some variables may not follow the common tree structure of the input data (sets $\Omega^{w'}_{w,t}$, $\Omega^{w'}_{w,dg}$, and $\Omega^{w'}_{w,mg}$). For this formulation, the variable that requires special attention is the monthly TPA capacity contracting $mT_{w,x,mg}$ for which a specific set $mT\Omega^{w''}_{w,mg}$ may need to be considered in equations (3.4) and (3.11), replacing them with (3.21) and (3.22), respectively (the changes are highlighted in blue).

$$csT_{w,x,mg} = \sum_{\substack{dg \in \Omega^{dg}_{mg} \\ w' \in \Omega^{w'}_{w,dg}}} [cnX_{w',x,dg} \cdot Tu_{x,mg} + dT_{w',x,dg} \cdot Td_{x,mg}] + mT_{w'',x,mg} \cdot Tm_{x,mg}$$
$$\forall w \in \Omega^{w}_{mg}, w'' \in mT\Omega^{w''}_{w,mg}, x \in X, mg \in MG \quad (3.21)$$

$$cnX_{w',x,dg} \leq dT_{w',x,dg} + Tp_{x,dg} + mT_{w'',x,mg}$$
$$\forall w \in \Omega^{w}_{mg}, w' \in \Omega^{w'}_{w,dg}, w'' \in mT\Omega^{w''}_{w,mg}, x \in X, dg \in \Omega^{dg}_{mg}, mg \in MG \quad (3.22)$$

Specifically, for the case example presented in the following section, with the tree structure in Figure 3.5, monthly decisions for the second month are considered common to all scenarios. Therefore the definition of the set $mT\Omega^{w''}_{w,mg}$ is the following:

- $mg \in \{1, 2\}, w \in W, w'' = 1 \rightarrow w'' \in mT\Omega^{w''}_{w,mg}$
- $mg = 3, w = w'' \rightarrow w'' \in mT\Omega^{w''}_{w,mg}$

3.4.5 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, labeled as A, Bfix, B, and C, are explained below, and the equations included in each one are detailed in Table 3.1.

Model A:

Model using the standard stochastic self-UC formulation that represents each generator's costs with a commitment cost and a variable cost.

Model 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.

Model 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. The main difference with model Bfix regarding the used variables is that $qb_{w,dg}$ depends on index b becoming $qb_{w,dg,b}$. The possibility to sell gas represented by the variable $qs_{w,dg,b}$ is fixed to 0 in this case.

Model C:

Same model as B but allowing gas sales ($qs_{w,dg,b} \geq 0$).

Table 3.1: Equations in each model.

Constraints	Model A	Model Bfix	Model B	Model C	Technical constraints included in all models
(3.1)	✓	✓	✓	✓	
(3.2)	✓				
(3.3)		✓	✓	✓	
(3.4)		✓	✓	✓	
(3.5)		✓	✓	✓	
(3.6)		✓			(A.9)
(3.7)		✓	✓	✓	(A.10)
(3.8)		✓	✓	✓	(A.11)
(3.9)		✓	✓	✓	(A.12)
(3.10)		✓	✓	✓	(A.13)
(3.11)		✓	✓	✓	(A.14)
(3.12)		✓	✓	✓	(A.15)
(3.13)		✓	✓	✓	(A.16)
(3.14)		✓			(A.17)
(3.15)		✓	✓	✓	(A.18)
(3.16)			✓	✓	
(3.17)			✓	✓	
(3.18)			✓	✓	
(3.19)			✓	✓	
(3.20)			✓	✓	
$qs_{w,dg,b}$	-	-	$= 0$	≥ 0	

3.5 Case Study

This section presents an example case and compares the results that the presented models obtain. First, the data of the case are presented. Then, comparisons between models are analyzed. The most interesting 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 illustrates 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.

3.5.1 Data

The case study data consists of 6 CCGT units that have fictional but realistic characteristics shown in Table 3.2. 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 29 September 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 Transmission System Operator (TSO) Enagás (Enagás, 2018) and is presented in Table 3.3 and Table 3.4. CO_2 price (19.56€/ton) has been taken from SENDECO2 (Sistema Europeo de Negociación de CO2 (SENDECO2), 2018). Electricity and gas price scenarios are explained in Section 3.5.1.1 Scenario tree construction.

The technical characteristics of the generation units as well as the gas and electricity prices for the 210 generated scenarios, the reduced scenario trees, and the real prices, that are going to be explained in next section, are available online in (Otaola-Arca, 2022a).

3.5.1.1 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) (S. Zhou et al., 2019) and Gated Recurrent Units (GRU) (Bottieau et al., 2020) 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, (Mercado Ibérico del Gas (MIBGAS), 2018)) was added to the list of explanatory variables by replicating the daily price to all the corresponding hours of each day. During the training and validation phase, the usual process of using part of the dataset for training and another part for validation was followed. After training the model, synthetic time

Table 3.2: Generators' characteristics.

Parameters	Units	G1	G2	G3	G4	G5	G6
$\underline{P_g}$	[MW]	128.33	195.00	200.00	135.00	195.00	200.00
$\overline{P_g}$	[MW]	385.00	390.00	400.00	405.00	390.00	400.00
RU_g	[MW/h]	55.00	70.00	74.00	76.00	70.00	74.00
RD_g	[MW/h]	55.00	70.00	74.00	76.00	70.00	74.00
$TmnOn_g$	[h]	2	2	2	2	2	2
$TmnOff_g$	[h]	2	3	3	2	3	3
$PSU_{g,tu=1}$	[MWh]	50.00	50.00	50.00	50.00	50.00	50.00
$PSU_{g,tu=2}$	[MWh]	-	127.00	131.40	-	127.00	131.40
$PSD_{g,td}$	[MWh]	0.00	0.00	0.00	0.00	0.00	0.00
TSU_g	[h]	1	2	2	1	2	2
TSD_g	[h]	1	1	1	1	1	1
IS_g	0,1	0	0	0	0	0	0
IP_g	[MW]	0.00	0.00	0.00	0.00	0.00	0.00
TUo_g	[h]	0	0	0	0	0	0
TDo_g	[h]	24	24	24	24	24	24
$TmnS_{g,su=1}$	[h]	0	0	0	0	0	0
$TmnS_{g,su=2}$	[h]	12	12	12	12	12	12
$TmnS_{g,su=3}$	[h]	24	24	24	24	24	24
$CSmn_g$	[k€/h]	7.989	11.975	12.457	9.312	11.975	12.457
$CSvr_g$	[€/MWh]	43.21	43.88	45.19	44.86	43.88	45.19
$CSsu_{g,su=1}$	[k€]	16.035	17.106	17.107	19.231	17.107	17.107
$CSsu_{g,su=2}$	[k€]	22.330	23.660	23.660	26.360	23.660	23.660
$CSsu_{g,su=3}$	[k€]	28.624	30.212	30.212	33.489	30.212	30.212
$CSsd_g$	[k€]	1.916	1.835	1.835	1.846	1.835	1.835
$CNmn_g$	[$\mathrm{MWh_t}$/h]	255.16	396.93	414.03	302.32	396.93	414.03
$CNvr_g$	[$\mathrm{MWh_t}$/MWh]	1.54	1.56	1.60	1.59	1.56	1.60
$CNsu_{g,su=1}$	[$\mathrm{MWh_t}$]	436.13	465.20	465.20	523.35	465.20	465.20
$CNsu_{g,su=2}$	[$\mathrm{MWh_t}$]	654.19	697.80	697.80	785.03	697.80	697.80
$CNsu_{g,su=3}$	[$\mathrm{MWh_t}$]	872.25	930.41	930.41	1046.71	930.41	930.41
$CNsd_g$	[$\mathrm{MWh_t}$]	65.13	65.13	65.13	65.13	65.13	65.13
OMh_g	[€/h]	800	800	800	800	800	800
$OMsu_g$	[€]	4000	4000	4000	4000	4000	4000
$CO2r_g$	[ton/$\mathrm{MWh_t}$]	0.202	0.203	0.205	0.206	0.211	0.212

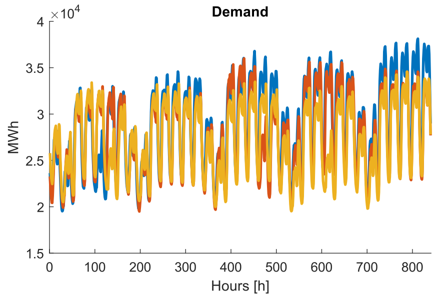
Table 3.3: Third Party Access data.

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

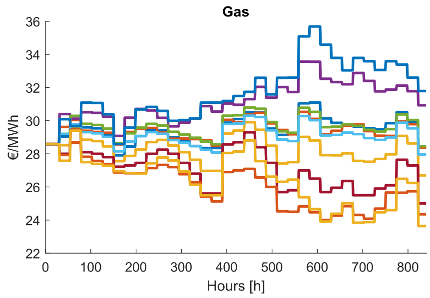
Table 3.4: Storage data.

$Sd_{x,mg}$ [€/$\mathrm{MWh_t}$]	$Sm_{x,mg}$ [€/$\mathrm{MWh_t}$]	$Sp_{x,dg}$ [$\mathrm{MWh_t}$]	Si_x [€/$\mathrm{MWh_t}$]	Se_x [€/$\mathrm{MWh_t}$]
0.037	0.534	0.000	0.244	0.131

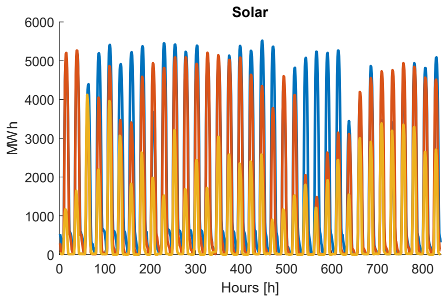
series based on historical records of gas price, wind, solar, and demand were sampled to have enough uncertainty representation. Different combinations of these data series, displayed in Figure 3.4, were used as input data by the GRU model resulting in a total number of 210 scenarios. Each one of those scenarios is a pair of electricity and gas time series that cover the considered 5-week horizon, and that can be characterized by a given probability. The 210 scenarios obtained by this process were thought to represent the uncertainty at an acceptable level. Since uncertainty modeling is not the main focus of this thesis, no additional quality evaluations were performed.



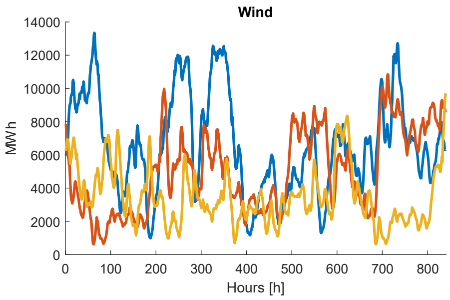
(a) Demand data.



(b) Gas prices data.



(c) Solar generation data.



(d) Wind generation data.

Figure 3.4: Explanatory variables data.

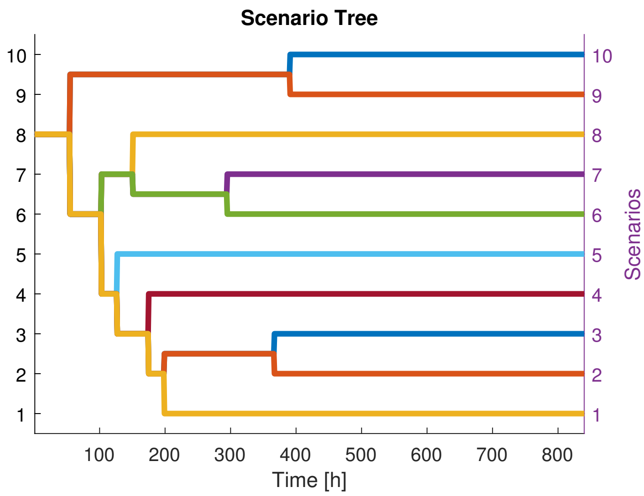
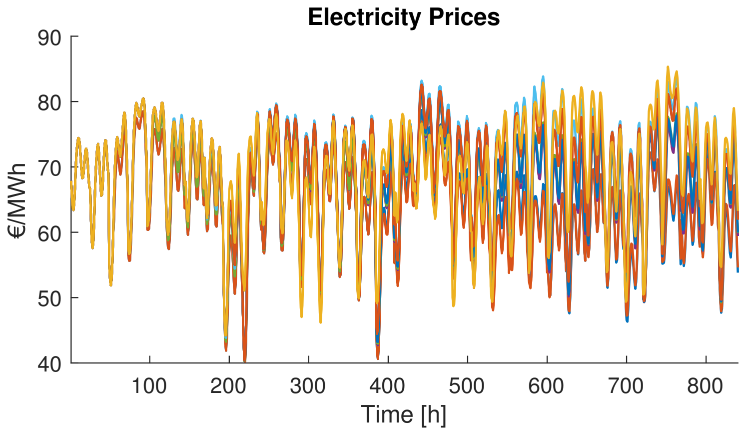
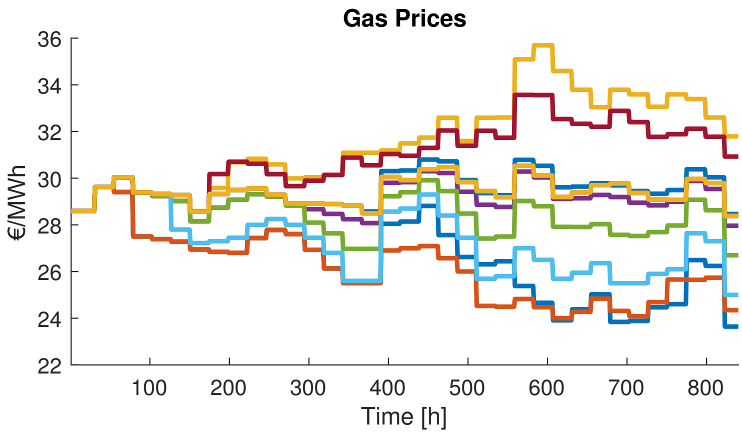


Figure 3.5: Scenario tree.

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 (Dupačová et al., 2003) and (Heitsch & Römisch, 2003). After testing three options (3, 10, and 50 scenarios), the total number of final scenarios to be considered in the stochastic formulation was set to 10 due to the complexity of the problem. The branching of the different scenarios was only allowed at the beginning of each day during the first three weeks. Figure 3.5 shows the structure of the obtained tree, and Figure 3.6 shows the reduced scenarios of electricity (Figure 3.6a) and gas (Figure 3.6b) prices. 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.



(a) Electricity day-ahead market prices.



(b) Gas market prices.

Figure 3.6: Gas and electricity market prices for the scenario tree.

Regarding the tree implementation, all decision variables follow the same structure presented in Figure 3.5, except for the monthly capacity. The simulation ends October with more than one scenario. Therefore, the monthly decision variables could depend on the scenarios. However, as one of the objectives is precisely to determine the amount of monthly capacity to contract at the beginning of the month, in this example case, we must establish a specific set $mT\Omega^{w'}_{w,mg}$ (following the explanation in Appendix A.2

Uncertainty formulation) where:

$$w' \in mT\Omega_{w,mg}^{w'} \quad \rightarrow \quad w' = 1 \quad \forall w \in \Omega_{mg}^{w}, mg = 2$$

3.5.2 Models A vs. Bfix

The process to calculate the values of the cost parameters $CSmn_g$, $CSvr_g$, $CSsd_g$ and $CSsu_{g,su}$ that has been used to model the cost of the units in model A is presented in Listing 1. By performing such calculation, 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.

```
run_model(Bfix)
for g in G:
    for p in data_point:
        hourly_cost [p] = (
              TPA cost          #proportional to hourly consumption of g
            + Gas storage cost #proportional to hourly consumption of g
            + Supply cost      #proportional to hourly consumption of g
            + Emissions cost
            + OM cost)
    (CSvr,CSmn,CSsu,CSsd) = linear_regression(power_output, hourly_cost)

def linear_regression(power, cost):
    Perform a linear regression of the points [power, cost]
    var = slope of the linear equation
    min = cost value that corresponds to the minimum stable load Pmin
    start = weighted average of the hourly cost incurred when starting up
    stop = weighted average of the hourly cost incurred when shutting down
    return (var,min,start,stop)
```

Code 1: Pseudocode to compute the cost parameters for model A.

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 3.5. 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 (Mercado Ibérico del Gas (MIBGAS), 2018) and electricity (Operador del Mercado Ibérico de Energía - Polo Español (OMIE), 2018) during the horizon under study. As shown in the rows labeled as "Real" in Table 3.5, model Bfix obtains results that are 4.21% better than model A.

We can extrapolate these results and calculate the values of the annualized magnitudes. The profits obtained with the modeling that represents the TPA tariffs in detail are 7.48M€/year higher for the stochastic solution and 3.43M€/year higher when facing the actual prices with the out-of-sample analysis.

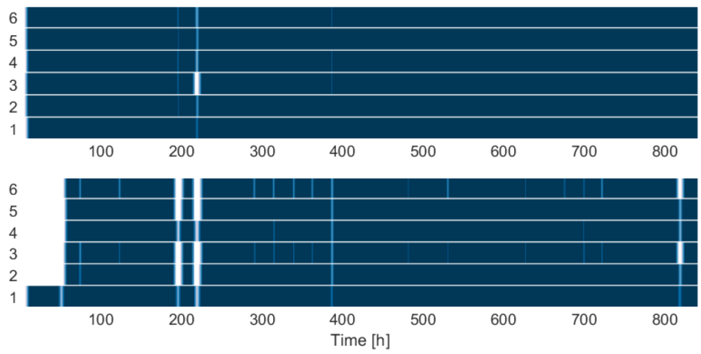
Table 3.5: Global results for models A and Bfix.

	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

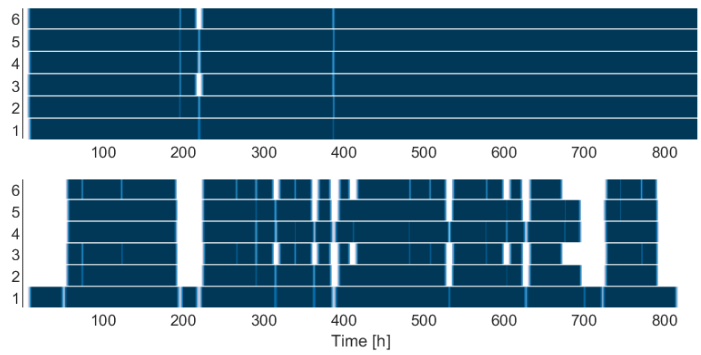
In order to compare the different hourly scheduling between models A and Bfix (considering model Bfix as the best solution when arbitrage is not allowed) the deviation between their electricity generation has been calculated using the formula in (3.23). The results show that model A has a difference in unit scheduling of 13.05% against model Bfix. In that formula, $pt^{M}_{w,g,t}$ represents the power output of each generator g in the hour t for the scenario w as a result of the models Bfix and A.

$$\frac{100 \cdot \sum_{w \in W} \left[Prob_w \cdot \sum_{\substack{g \in G \\ t \in T \\ w' \in \Omega^{w'}_{w,t}}} \left[\frac{\left| pt^{Bfix}_{w',g,t} - pt^{A}_{w',g,t} \right|}{\overline{P_g}} \right] \right]}{n^{\text{o}}{}_{hours} \cdot n^{\text{o}}{}_{generators}} \tag{3.23}$$

Figure 3.7 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 (3.23). 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 electricity in scenario 5 (Figure 3.7a) which has higher electricity prices and lower gas prices than scenario 8 (Figure 3.7b). 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.



(a) Scenario 5. A top, Bfix bottom.



(b) Scenario 8. A top, Bfix bottom.

Figure 3.7: CCGTs power output for models A and Bfix.

Some small decreases in load for model Bfix can be appreciated in Figure 3.7. To better understand the power output of the units and the reason for those changes, a more detailed representation is shown in Figure 3.8. 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 33.98GWh. 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.

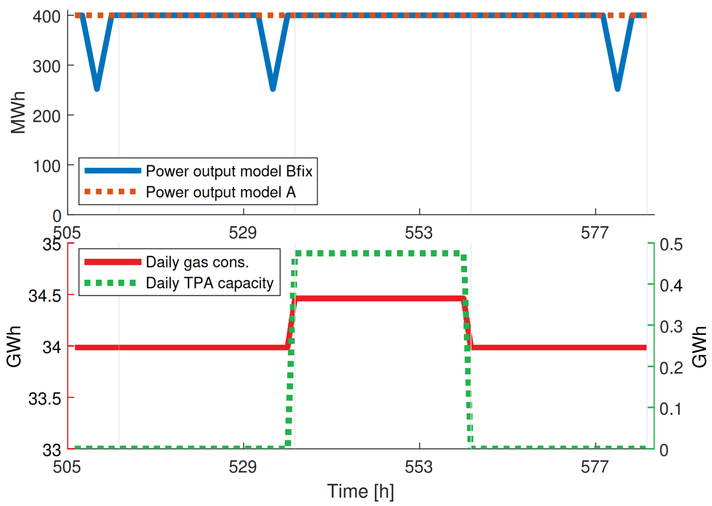
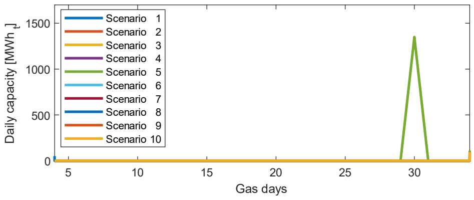


Figure 3.8: Unit 6 power output in models A and Bfix (top), and gas consumption and daily TPA capacity in model Bfix (bottom). Results for scenario 9. Grey vertical lines indicate gas days.

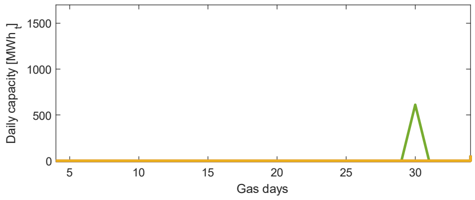
Regarding the combination of daily and monthly TPA capacities contracted, Figure 3.9 shows the daily TPA capacity contracted for each scenario in October and Table 3.6 shows the monthly alternative. With respect to the monthly capacity, the simulation period starts in the end of September and therefore no monthly contracting is possible for that month; in October, due to the nonanticipativity constraint, the same capacity is contracted for all scenarios; and 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 3.6: Monthly TPA contracted in October.

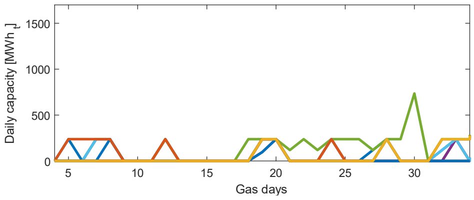
Exit points	GWh_t
G1 & G2	32.40
G3	17.40
G4	17.58
G5 & G6	33.98



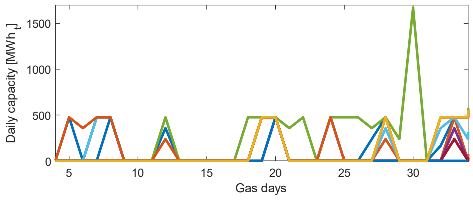
(a) Exit point of units G1 & G2.



(b) Exit point of unit G4.



(c) Exit point of unit G3.



(d) Exit point of units G5 & G6.

Figure 3.9: Daily TPA capacity contracted for October at each exit point, for all scenarios.

3.5.3 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 3.7. Gas blocks quantity is fixed to 30GWh and a maximum of 270GWh is available to buy/sell each day.

Table 3.7: Gas price factors for each gas block.

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

The comparison between models B and C is focused on the interaction of markets. Table 3.8 presents the main global results and Figure 3.10 shows graphical results for one of the scenarios.

Table 3.8: Global results for models B and C. Expected Value (EV) and σ (standard deviation).

	B		C	
	EV	σ	EV	σ
Electricity spot market				
Income [M€]	88.00	16.20	87.68	19.01
Gas used [GWh_t]	2279.97	424.25	2271.05	496.92
Electricity generation [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_t]	2279.97	424.25	2343.92	369.00
Sold gas [GWh_t]	0.00	0.00	72.87	147.92
Regulated cost				
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 cost [M€]	83.98	13.50	85.93	12.06
Total profits [M€]	4.02	3.20	4.13	3.10

From the results presented in Table 3.8 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. Figure 3.10 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.

Finally, the size of the problem is not negligible, as can be observed in Table 3.9. Such size results from optimizing a 5-week horizon to fit an entire gas month and the use of a stochastic formulation to deal with the uncertainty, which can not be disregarded in such a long horizon.

Table 3.9: Problem size for models B and C.

[no. thousands]	rows	columns	nonzeros	binaries
Model B	410	280	237	235
Model C	410	283	238	235

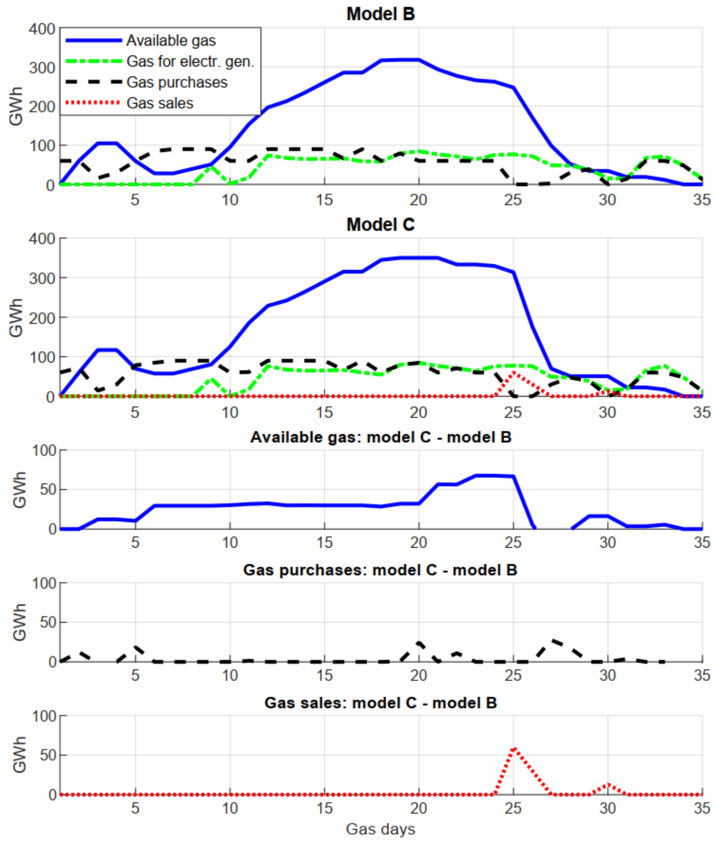


Figure 3.10: Gas storage, purchases, sales, usage for electricity generation, and their differences for models B and C for in scenario 4.

3.6 Conclusions

CCGTs will play an important role in the energy transition. This chapter highlights the importance of representing in an accurate manner the costs incurred by a GenCo 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 chapter 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 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 TPA, and also to take advantage of storage services available in the infrastructure to increase their profits.

Chapter 4

Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology

The developments presented in this chapter are reflected in the paper *"Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology"*, submitted to Institute of Electrical and Electronics Engineers (IEEE) Transactions on Power Systems on 28 February 2022.

4.1 Introduction

Section 1.5 Taxes involved in electricity generation describes the main categories of taxes that can be applied to Generation Companies (GenCos) operating in current power markets. In addition, Section 1.5.1 The Spanish case has explained in detail the existing tax scheme in Spain as a real example. From the modeling point of view, the base variable used to calculate the tax is more important than its nature. The most common charges are usually applied based on the following concepts: fuel consumption, greenhouse gas emissions, electricity generation, and revenues from electricity generation. Among all of them, the most challenging from a mathematical point of view is the levy applied to market revenue for those GenCos that are price-makers, as they depend on a variable that is not known a priory and depends on the GenCos own operation.

In Section 2.4 Strategic behavior, we have reviewed the state-of-the-art regarding income representation for price-maker agents. Specifically, certain disadvantages of the commonly used formulations that compute revenues at the portfolio level have been analyzed in Section 2.4.2 Drawbacks of the formulation based on income functions. Such drawbacks include the shared ownership of generating units and income-based taxes.

In this chapter, we propose a complete stochastic self Unit Commitment (self-UC) formulation to find the optimal Unit Commitment (UC) and hourly scheduling from the perspective of an individual price-maker agent participating in the market. This formulation is helpful for both GenCos in planning their operation and regulators and system operators in analyzing the expected behaviors of such GenCos.

The formulation uses discretized residual demand curves with the binary expansion method for revenue representation. The main idea is to represent the revenues of each generator individually, which allows to correctly account for both the actual revenues derived from shared units and the true costs associated with all tax categories, including levies applied to market revenues. As this thesis is focused on electricity generation using thermal units, no hydro generation is included in the formulation. However, all taxes that may exist for hydro units are already covered in the proposed formulation.

The remaining of this chapter is organized as follows:

- Section 4.2 Mathematical formulation presents the traditional and proposed formulations, explaining in detail how they work.
- Section 4.3 Case Study shows a study case where the formulations are compared stating the lacks of the current approaches and therefore highlighting the importance of the proposed solution.
- Section 4.4 Conclusion summarizes the main conclusions.

4.2 Mathematical formulation

In this section, we present the mathematical formulation of a self-UC model that helps a GenCo to find the optimal UC and hourly scheduling of its own generators in a market environment. Two versions of this formulation are presented, the usual approach that models revenues on an aggregate basis (Section 4.2.2 Formulation using income curves), and the formulation we propose that models revenues on an individual generating unit basis (Section 4.2.1 Proposed formulation).

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. are the ones presented in Appendix A.3 Unit Commitment technical constraints. Specifically, constraints (A.9), (A.10), (A.11), (A.12), (A.13), (A.14), (A.15), (A.16), (A.17), and (A.18) are used.

4.2.1 Proposed formulation

This formulation can accurately compute the individual revenue of each generation unit. For this purpose, it has the discretized residual demand curves as input data and uses the binary expansion technique. Section 4.2.1.1 Conceptual example explains how the formulation works using a simplified example, and Section 4.2.1.2 Constraints formulation presents the objective function and constraints formulation.

4.2.1.1 Conceptual example

In this example, there are three units (G1, G2, and G3) that have a maximum power output of 150MW, and produce 110, 120, and 150MWh, respectively. The residual demand curve is discretized with a fixed price step (0.2€) as in Figure 4.1. Each segment is defined by a minimum and maximum generation, and a market price.

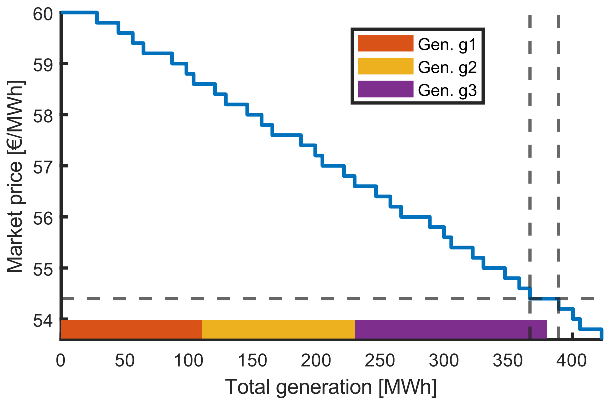


Figure 4.1: Discretized residual demand curve. The active segment depends on the total generation of the units. Dashed vertical lines indicate the upper and lower bounds of the active segment, and the dashed horizontal line corresponds to the resulting market price.

The idea is to define a possible output power for each generator and each step of the discretized residual demand function. Then, by means of some binary variable, only the active segment will be used to evaluate the actual output power and the corresponding income. Such active segment depends on the total generation of all the units, which is 370MWh for this example. Therefore, the active segment is the one defined by the dashed lines in Figure 4.1. Figure 4.2 shows the units' generation corresponding to each segment, where it can be seen that it is equal to zero for the non-active segments, and therefore, the total generation of each unit is assigned to the only active segment.

Having the generation depending on the residual demand segments allows us to compute the income of each unit by performing the summation over the residual demand segments of the energy in each segment (variable) times the price of each segment (parameter) as in (4.1).

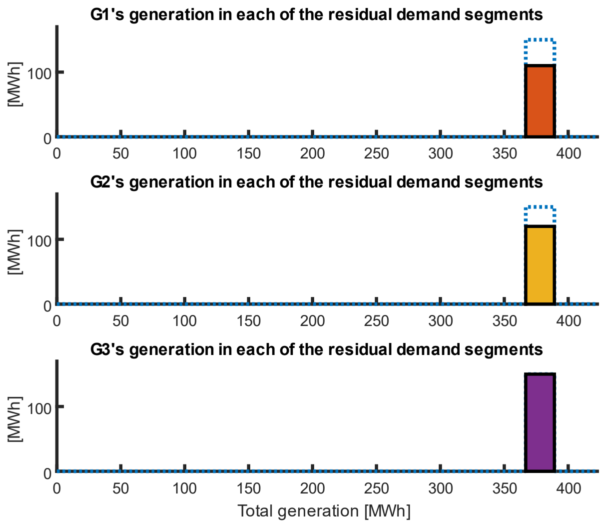


Figure 4.2: Maximum (dashed blue) and actual (color corresponding to the unit) generation in each segment of the residual demand curve. The maximum is equal to 0 for all segments that are not active.

$$income_g = \sum_{segment} [Price_{segment} \cdot generation_{segment,g}] \qquad \forall g \in G \quad (4.1)$$

4.2.1.2 Constraints formulation

As previously introduced, the residual demand curve is discretized with fixed steps in the price axis. In Figure 4.3 a discretization example is displayed.

The objective function (4.2) is to maximize the GenCo's expected profit: the sum extended to all its generators of the difference between incomes and costs and taxes multiplied by the scenario probability.

$$\max \left(\sum_{\substack{w \in W \\ w' \in \Omega_{w,t}^{w'} \\ g \in G \\ t \in T}} [Prob_w \left(incG_{w',g,t} - csG_{w',g,t} - txG_{w',g,t} \right)] \right) \quad (4.2)$$

The generators individual income (4.3) is the price of each residual demand curve segment times the power output in each segment. Notice that as this variable is defined for each generation unit, the potential reduction due to shared ownership can be easily

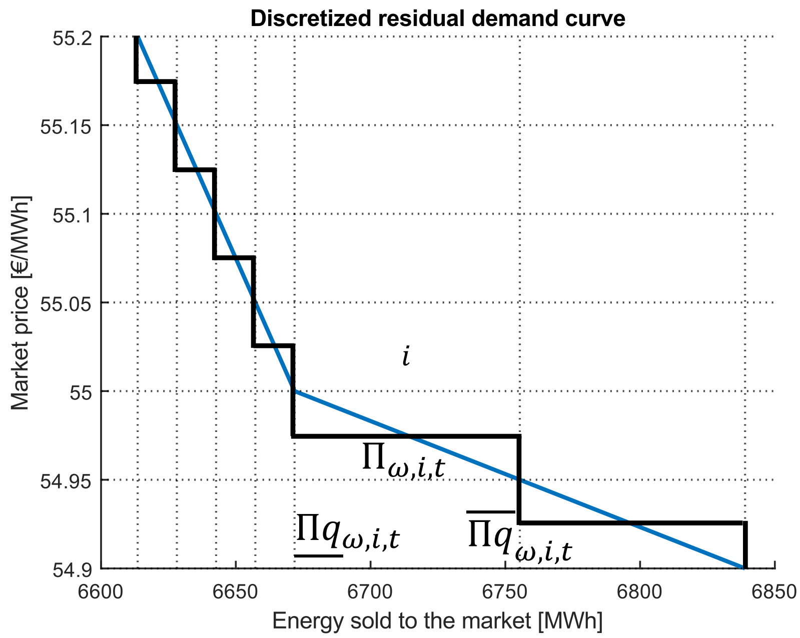


Figure 4.3: Residual demand curve discretization example with a 0.05€ step for a segment i. $RD\Pi^{E}_{w,i,t}$: segment price; $\underline{RDq}_{w,i,t}$: segment minimum power; $\overline{RDq}_{w,i,t}$: segment maximum power.

taken into account.

$$incG_{w,g,t} = Own_g \sum_{i \in \Omega^{i}_{w,t}} \left[RD\Pi^{E}_{w,i,t} \cdot apt_{w,i,g,t} \right] \qquad \forall w \in \Omega^{w}_{t}, g \in G, t \in T \quad (4.3)$$

Equation (4.4) ensures that only one segment of each residual demand curve is active for each time period.

$$\sum_{i \in \Omega^{i}_{w,t}} \left[a_{w,i,t} \right] = 1 \qquad \forall w \in \Omega^{w}_{t}, t \in T \quad (4.4)$$

Equations (4.5) and (4.6) locate the active segment i of the residual demand curve as a function of the total generation. 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 lower (higher) than the total generation.

$$\sum_{g \in G} [pt_{w,g,t}] \geq \sum_{i \in \Omega^i_{w,t}} \left[a_{w,i,t} \cdot \underline{RDq}_{w,i,t}\right] \qquad \forall w \in \Omega^w_t, t \in T \quad (4.5)$$

$$\sum_{g \in G} [pt_{w,g,t}] \leq \sum_{i \in \Omega^i_{w,t}} \left[a_{w,i,t} \cdot \overline{RDq}_{w,i,t}\right] \qquad \forall w \in \Omega^w_t, t \in T \quad (4.6)$$

The generator total power output (4.7) is equal to its power in all the residual demand curve segments:

$$pt_{w,g,t} = \sum_{i \in \Omega^i_{w,t}} [apt_{w,i,g,t}] \qquad \forall w \in \Omega^w_t, g \in G, t \in T \quad (4.7)$$

Equation (4.8) establishes the relation between the power output of the generator and the active residual demand curve segments:

$$apt_{w,i,g,t} \leq a_{w,i,t} \cdot \overline{P}_{g,t} \qquad \forall w \in \Omega^w_t, i \in \Omega^i_{w,t}, g \in G, t \in T \quad (4.8)$$

The Operation and Maintenance (O&M) cost of each generator (4.9) accounts for the hours of use and the number of start-up maneuvers.

$$csOM_{w,g,t} = Own_g \left(OMsu_g \cdot y_{w,g,t} + OMh_g \cdot v_{w,g,t}\right) \qquad \forall w \in \Omega^w_t, g \in G, t \in T \quad (4.9)$$

The fuel consumption of each generator is computed in (4.10), and its associated cost is calculated in (4.11).

$$\begin{aligned} cnG_{w,g,t} =& CNsd_g \cdot z_{w,g,t} + CNmn_g \cdot v_{w,g,t} + CNvr_g \cdot p_{w,g,t} \\ &+ \sum_{su} [CNsu_{g,su} \cdot \delta_{w,g,t,su}] \qquad \forall w \in \Omega^w_t, g \in G, t \in T \quad (4.10) \end{aligned}$$

$$csCN_{w,g,t} = Own_g \cdot cnG_{w,g,t} \cdot PCN_g \qquad \forall w \in \Omega^w_t, g \in G, t \in T \quad (4.11)$$

Regarding the calculation of the expenses, on the one hand, the cost of each generator is computed in (4.12) as the consumption cost plus the O&M cost. On the other hand, all the taxes applied to the generation unit are aggregated in (4.13). Notice that all those terms have already considered the ownership percentage of the units.

$$csG_{w,g,t} = csCN_{w,g,t} + csOM_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T \quad (4.12)$$

$$txG_{w,g,t} = txCN_{w,g,t} + txCO2_{w,g,t} + txE_{w,g,t} + txI_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T \quad (4.13)$$

The following equations compute the expenses for the different taxes that may exist. The fee from the tax applied to fuel consumption is calculated with the consumption variable and the tax rate (4.14). The expense of an emission tax is computed with the consumption variable, a ratio regarding emission per fuel consumption, and the emission tax rate (4.15). For the generation tax fee, the total generation of the unit and the tax rate are taken into account (4.16). Finally, the income tax expense uses the individual revenue variable and the income tax (4.17).

$$txCN_{w,g,t} = TxCN_g \cdot Own_g \cdot cnG_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T \quad (4.14)$$

$$txCO2_{w,g,t} = TxCO2 \cdot Own_g \cdot cnG_{w,g,t} \cdot CO2r_g \qquad \forall w \in \Omega_t^w, g \in G, t \in T \quad (4.15)$$

$$txE_{w,g,t} = TxE_g \cdot Own_g \cdot pt_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T \quad (4.16)$$

$$txI_{w,g,t} = TxI_g \cdot incG_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T \quad (4.17)$$

4.2.2 Formulation using income curves

The objective function (4.18) is to maximize the expected profits by subtracting the cost and the taxes to the revenue calculated with the income curve.

$$\max \left(\sum_{\substack{w \in W \\ w' \in \Omega_{w,t}^{w'} \\ t \in T}} \left[Prob_w \left(incT_{w',t} - \sum_{g \in G} [csG_{w',g,t} + txG_{w',g,t}] \right) \right] \right) \quad (4.18)$$

The revenue in each period (4.19) is computed as the income in each segment of the income curve.

$$incT_{w,t} = \sum_{s\in\Omega^s_{w,t}} [Islp_{w,s,t} \cdot qI_{w,s,t}] \qquad \forall w \in \Omega^w_t, t \in T \quad (4.19)$$

The total power generation of the units is equal to the power for the the income curve (4.20).

$$\sum_{g\in G} [pt_{w,g,t}] = \sum_{s\in\Omega^s_{w,t}} [qI_{w,s,t}] \qquad \forall w \in \Omega^w_t, t \in T \quad (4.20)$$

Equations (4.21) and (4.22) 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 $c = 1$:

$$qI_{w,s,t} \geq \left(\overline{Iq}_{w,s,t} - \underline{Iq}_{w,s,t}\right) qbinI_{w,c,t} \qquad \forall w \in \Omega^w_t, t \in T, (c,s) \in \Omega^{cs}_{w,t} \quad (4.21)$$

$$qI_{w,s,t} \leq \left(\overline{Iq}_{w,s,t} - \underline{Iq}_{w,s,t}\right) qbinI_{w,c-1,t} \qquad \forall w \in \Omega^w_t, t \in T, (c,s) \in \Omega^{cs}_{w,t} \quad (4.22)$$

Equation (4.23) establishes the order in which the concave intervals are activated. This equation is theoretically redundant with (4.21) and (4.22), 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.

$$qbinI_{w,c,t} \leq qbinI_{w,c-1,t} \qquad \forall w \in \Omega^w_t, t \in T, c \in \Omega^c_{w,t}, c > 1 \quad (4.23)$$

The generation costs are computed the same way as in the proposed formulation, using (4.12), where the fuel consumption and O&M costs are computed using (4.10), (4.11), and (4.9).

Regarding taxes, to accurately represent fuel consumption, carbon emissions, and electricity generation taxes, they should be calculated with the previously presented equations (4.14), (4.15) and (4.16). The resulting tax equation considering only these concepts would be (4.24a):

$$txG_{w,g,t} = txCN_{w,g,t} + txCO2_{w,g,t} + txE_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T \tag{4.24a}$$

Finally, income taxation should also be tackled. If the tax rate is exactly the same for all generating units, the precise way to express it would be to modify equation (4.19) 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. On top of multiplying the revenue by TxC an approximation for the remaining of the charge (tax applied to unit g minus common tax already included in the revenue calculation) could be considered using (4.25). The idea behind this approximation is to increase the expenses of each unit by a factor of $(1 - TxC)/(1 - TxI_g)$ as previously presented in Section 1.5. Therefore, the total tax expenses calculation (4.24a) should be substituted by (4.24b) to account for this approximation of the income tax.

$$txG_{w,g,t} = txCN_{w,g,t} + txCO2_{w,g,t} + txE_{w,g,t} + txIaprox_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T \tag{4.24b}$$

$$txIaprox_{w,g,t} = (csG_{w,g,t} + txCN_{w,g,t} + txCO2_{w,g,t} + txE_{w,g,t})\left(\frac{1 - TxC}{1 - TxI_g} - 1\right) \qquad \forall w \in \Omega_t^w, g \in G, t \in T \tag{4.25}$$

4.2.3 Stochastic particularities

In this case, we are not using a tree structure, but the different scenarios are considered from the start. Therefore, each scenario is represented by itself for the whole optimization period.

- $t \in T, w \in W, w' = w \rightarrow w' \in \Omega_{w,t}^{w'}$

However, there are some variables that require special attention: the commitment status ($v_{w,g,t}$), the start-up ($y_{w,g,t}$) and shut-down ($z_{w,g,t}$) decisions and the type of start-up ($\delta_{w,g,su,t}$). As this is a self-UC optimization for the day-ahead market with a time horizon of 24 hours, the values of those variables have to be common to all scenarios. Therefore, a new set $u\Omega_{w,t}^{w'}$ has to be defined in order to establish that every scenario is represented by scenario $w = 1$.

- $t \in T, w \in W, w' = 1 \rightarrow w' \in u\Omega_{w,t}^{w'}$

Accordingly, equations including commitment-related variables have to be modified. The equations subject to be changed are: (A.9), (A.10), (A.11), (A.12), (A.13), (A.14), (A.15), (A.16), (A.18), (A.17), (4.9) and (4.10). Among all those equations, we show the modifications that have to be performed in the two that have been presented in this chapter as example: (4.9) and (4.10) have to be replaced with (4.26) and (4.27) (the changes are highlighted in blue). Notice that in equation (4.26) the only variables used to compute $csOM_{w,g,t}$ are $v_{w,g,t}$ and $y_{w,g,t}$. Therefore, it would be possible to apply the set $u\Omega^{w'}_{w,t}$ also to $csOM_{w,g,t}$. However, to keep the formulation clearer, no additional changes have been made. Following this explanation the reader may want to ask why $u\Omega^{w'}_{w,t}$ is used with $y_{w,g,t}$, $z_{w,g,t}$ and $\delta_{w,g,su,t}$ if the intention was to keep the formulation as clear as possible, and just by appliying it to $v_{w,g,t}$ the constraints would do the rest. It is, in fact, a very reasonable question, and the answer is that we preferred to treat all commitment-related variables in the same way as they share their nature.

$$
\begin{aligned}
csOM_{w,g,t} =& Own_g \left(OMsu_g \cdot y_{w',g,t} + OMh_g \cdot v_{w',g,t} \right) \\
& \qquad \forall w \in \Omega^w_t, w' \in u\Omega^{w'}_{w,t}, g \in G, t \in T
\end{aligned}
\tag{4.26}
$$

$$
\begin{aligned}
cnG_{w,g,t} =& CNsd_g \cdot z_{w',g,t} + CNmn_g \cdot v_{w',g,t} + CNvr_g \cdot p_{w,g,t} \\
& + \sum_{su} \left[CNsu_{g,su} \cdot \delta_{w',g,t,su} \right] \\
& \qquad \forall w \in \Omega^w_t, w' \in u\Omega^{w'}_{w,t}, g \in G, t \in T
\end{aligned}
\tag{4.27}
$$

On the one hand, the use of $u\Omega^{w'}_{w,t}$ gives flexibility to the formulation and enables the time horizon to be extended, for example, to cover two days. The duplication of the time horizon entails an increment in computational burden but gives economic value to the commitment status at the end of the first day. In that case, the commitment-related variables would be common to all scenarios during the first day, whereas they could take different values for the scenarios during the second day. On the other hand, if we are not interested in such flexibility, another more straightforward approach to avoid the use of $u\Omega^{w'}_{w,t}$ would be just to eliminate the scenario dependence of the commitment-related variables:

- $v_{w,g,t} \rightarrow v_{g,t}$
- $y_{w,g,t} \rightarrow y_{g,t}$
- $z_{w,g,t} \rightarrow z_{g,t}$
- $\delta_{w,g,t} \rightarrow \delta_{g,t}$

A similar idea could be applied to all remaining variables. As for the case example no tree structure is going to be used, all tree structure dependences using sets Ω could be removed and use $w \in W$ instead.

4.3 Case Study

This section presents an example case and compares the results that the two presented formulations obtain. In addition, specific aspects are analyzed by making some variations on the data to highlight the importance of the proposed formulation. First, the data of the case are presented. Then, it is shown that both formulations are equivalent when facing a case without the particularities that the traditional formulation is not able to cover. Finally, those cases in which the conventional formulation has problems are analyzed, showing how the proposed formulation solves them.

4.3.1 Setup and data

The model has been implemented in Python 3.8.5 using the Pyomo 5.7 package. Gurobi 9.03 was used as solver with a target MIPGap of 0.1%. The model was executed in a computer with the following characteristics:

- CPU: Intel Core i7-6700 Skylake at 3.40GHz. Gurobi was allowed to use 7 of its 8 threads.

- RAM: 2 x M378A2K43CB1-CRC 16GB at 1063MHz.

All the data used for this case study are online available in (Otaola-Arca, 2022b) unless explicitly indicated. The characteristics of the units are shown in Table 4.1, and CO_2 tax is $TxCO2 = 21$ €/ton. The residual demand curves for the Iberian market have been obtained with the model presented in (Portela González et al., 2017) and are displayed in Figure 4.4.

4.3.2 Income curve vs. individual income with 100% ownership and equal taxes for all generators

This subsection presents a comparison between the two models, the one that uses the income curve and the one that discretizes the residual demand curve to obtain the individual income per group. In this comparison, 100% ownership has been introduced as data for all groups, as well as a 5% generation tax, also equal for all groups. It has been modeled using the maximum detail, i.e. using 180 segments to represent the income curve and discretizing the residual demand curve with a step of 0.01€. The results of this comparison are presented in Table 4.2 and the resulting generation schedule is displayed in Figure 4.5. Magnitudes *"optimized"* are the values obtained by the optimizer, whereas magnitudes *"ex-post"* are the actual 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 chapter. In that case, the state-of-the-art approach should be preferred as

Table 4.1: Generation units data.

Parameters	Units	G1	G2	G3	G4	G5
$\underline{P}_g$	[MW]	128	200	185	185	180
$\overline{P}_g$	[MW]	385	400	390	390	400
RU_g	[MW/h]	55	74	70	70	70
RD_g	[MW/h]	55	74	70	70	70
$TmnOn_g$	[h]	2	2	2	2	2
$TmnOff_g$	[h]	2	3	3	3	3
$PSU_{g,tu=1}$	[MW]	128.0	131.4	127.0	127.0	127.0
$PSU_{g,tu=2}$	[MW]	-	200.0	185.0	185.0	180.0
$PSD_{g,td=1}$	[MW]	0.0	0.0	0.0	0.0	0.0
TSU_g	[h]	1	2	2	2	2
TSD_g	[h]	1	1	1	1	1
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
$TmnS_{g,su=1}$	[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
$CNmn_g$	[$\mathrm{MWh_t}$/h]	304	435	450	450	445
$CNvr_g$	[$\mathrm{MWh_t}$/MWh]	1.59	1.30	1.60	1.60	1.50
$CNsu_{g,su=1}$	[$\mathrm{MWh_t}$]	537	549	572	572	558
$CNsu_{g,su=2}$	[$\mathrm{MWh_t}$]	726	729	675	675	747
$CNsu_{g,su=3}$	[$\mathrm{MWh_t}$]	1026	983	1076	1076	1008
$CNsd_g$	[$\mathrm{MWh_t}$]	67.83	65.85	65.30	65.30	63.50
$CO2r_g$	[ton/$\mathrm{MWh_t}$]	0.19	0.19	0.19	0.19	0.19
$TxCN_g$	[€/$\mathrm{MWh_t}$]	2.5	2.5	2.5	2.5	2.5
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
PCN_g	[€/$\mathrm{MWh_t}$]	20	20	20	20	20
Own_g	[p.u.]	1.00	0.90	1.00	1.00	1.00

the number of variables and the computational time is smaller.

4.3.3 Income curve vs. individual income with <100% ownership and different taxes for the generators

In this subsection, the same comparison has been made as in the previous one, but for a case in which the ownership of the groups are not 100%, and the generation taxes are not the same for all groups. The data used are presented in (Otaola-Arca, 2022b); specifically, the changes with respect to the previous subsection are the following:

- Ownership (Own_g) of unit G2: 100% → 90%.
- Income tax (TxI_g) of unit G3: 5% → 4%.
- Income tax (TxI_g) of unit G4: 5% → 1%.

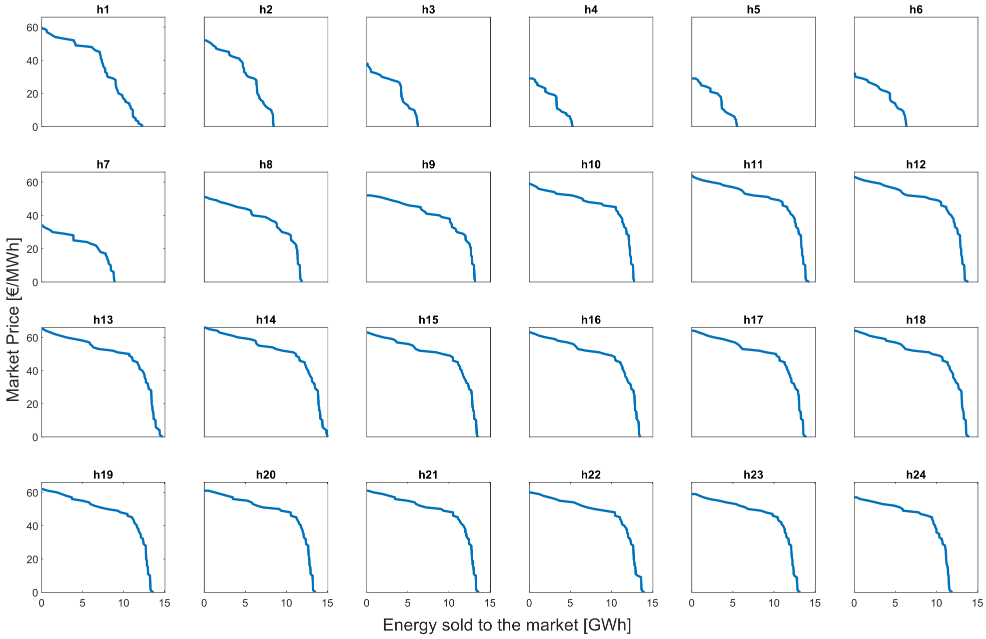


Figure 4.4: Residual demand curves for the 24 hours of the day (15/07/2013 Iberian system).

Table 4.2: Model comparison with Own_g=1 p.u., TxE_g=0.05 p.u., and maximum level of detail (180 seg and 0.01 €). Ex-post terms are calculated with the non-discretized original curves.

	Individual income	Income curve
Problem characteristics		
Discretization	0.01 [€]	180 [seg]
Continuous var. no.	126230	5089
Binary var. no.	25793	5040
Resolution Time [s]	450.7	7.4
OPTCR [%]	0.00	0.00
Optimized results		
Energy sold [GWh]	23.93	23.94
Income [k€]	1421.27	1420.57
Taxes [k€]	280.61	280.57
Cost [k€]	1046.66	1046.67
Profits [k€]	94.00	93.32
Ex-post results		
Income [k€]	1421.25	1421.28
Taxes [k€]	280.60	280.61
Cost [k€]	1046.66	1046.67
Profits [k€]	93.99	93.99

The results of this comparison are gathered in Table 4.3 and the resulting generation schedule is displayed in Figure 4.6.

In this case, differences can be observed in the resulting schedule, and therefore in

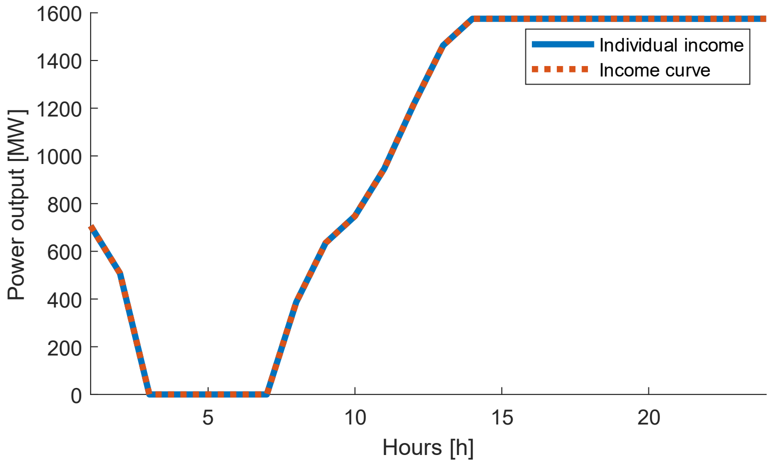


Figure 4.5: Total generation for both models with Own_g=1 p.u., TxE_g=0.05 p.u., and maximum level of detail (180 seg and 0.01 €).

Table 4.3: 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.

	Individual income	Income curve
Problem characteristics		
Discretization	0.01 [€]	180 [seg]
Continuous var. no.	126230	5089
Binary var. no.	25793	5040
Resolution Time [s]	276.6	52.0
OPTCR [%]	0.00	0.00
Optimized results		
Energy sold [GWh]	23.93	23.94
Income [k€]	1383.22	1378.39
Taxes [k€]	270.26	265.77
Cost [k€]	1020.75	1017.40
Profits [k€]	92.22	95.82
Ex-post results		
Income [k€]	1383.20	1378.51
Taxes [k€]	270.26	269.39
Cost [k€]	1020.75	1017.40
Profits [k€]	92.20	91.72

the profits obtained by each one of the models. From the analysis of Table 4.3 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

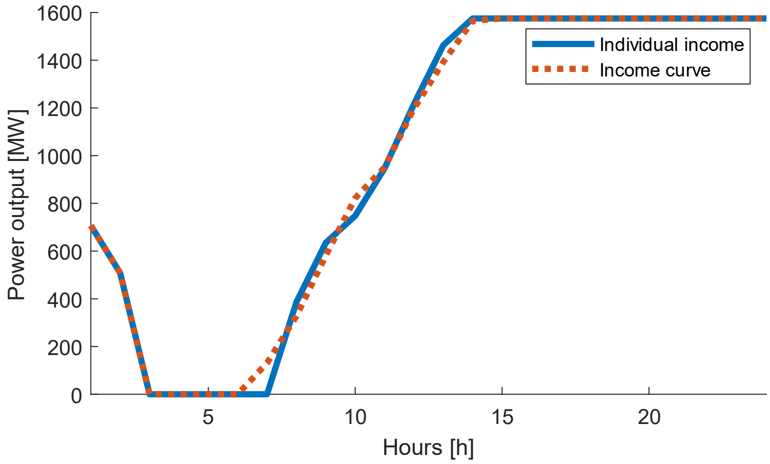


Figure 4.6: Total generation for both models with different values of Own_g and TxE_g, and maximum level of detail (180 seg and 0.01 €).

approach that uses the income curve.

We can extrapolate these results and calculate the values of the annualized magnitudes. On the one hand, the profits obtained with the detailed modeling using the residual demand curves are 175k€/year higher. On the other hand, regarding the errors of the models, the difference between the model's objective function and the result computed with the original residual demand curves is 7.3k€/year when using discretized residual demand curves, which is much lower than the 1.5M€/year error incurred when using income curves.

In addition, the individual income model is able to capture certain changes in scheduling that may result from a change in generation taxes, which the income curve model does not capture. The income curve model does not have such sensitivity because it approximates the impact of the tax (of groups that do not have the same tax as the one applied to the income curve itself), and therefore does not see the change as the price varies. To understand in detail how the model would capture these changes, some variations are analyzed. Those variations consist of modifying the tax schemes according to table Table 4.4. It is important to note that generations units G3 and G4 are technically identical.

With the tax scheme of case A the obtained schedule is the one shown in Figure 4.7a. Unit G4 remains off all day whereas G3 has the energy profile presented in Table 4.5. The expense of generating with G3 is cheaper than what would be the expense of generating that same power output with G4.

On the other hand, Figure 4.7b 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 expense is higher than that of

Table 4.4: Generation expenses for different taxes and prices. Cases A and B use the obtained price whereas case C has a 11.48% higher price.

	TxI_g [%]	TxE_g [€/MWh]	TxI_g [k€]	TxE_g [k€]	Total [k€]
Case A					
G3	4.00	1.00	12.839	5.367	18.206
G4	1.00	3.00	3.210	16.101	19.311
Case B					
G3	4.50	1.00	14.443	5.367	19.810
G4	1.00	3.00	3.210	16.101	19.311
Case C					
G3	4.00	1.00	14.313	5.367	19.680
G4	1.00	3.00	3.578	16.101	19.679

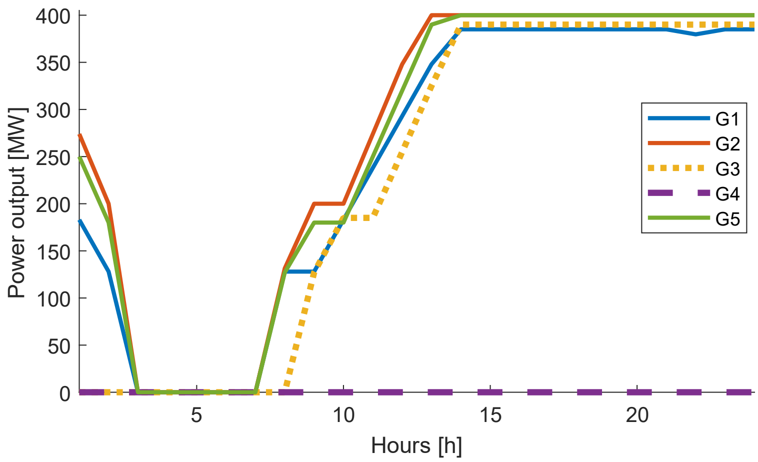
Table 4.5: G3/G4 generation profile depending on which one is connected.

Hour [h]	Price [€/MWh]	Generation [MWh]	Hour [h]	Price [€/MWh]	Generation [MWh]
1	56.77	0	13	62.25	325
2	51.16	0	14	64.05	390
3	38.30	0	15	60.61	390
4	29.49	0	16	60.55	390
5	29.56	0	17	61.75	390
6	32.15	0	18	61.57	390
7	34.86	0	19	60.26	390
8	50.56	0	20	59.59	390
9	51.83	127	21	59.33	390
10	57.43	185	22	58.20	390
11	61.66	185	23	56.83	390
12	60.96	255	24	55.14	390

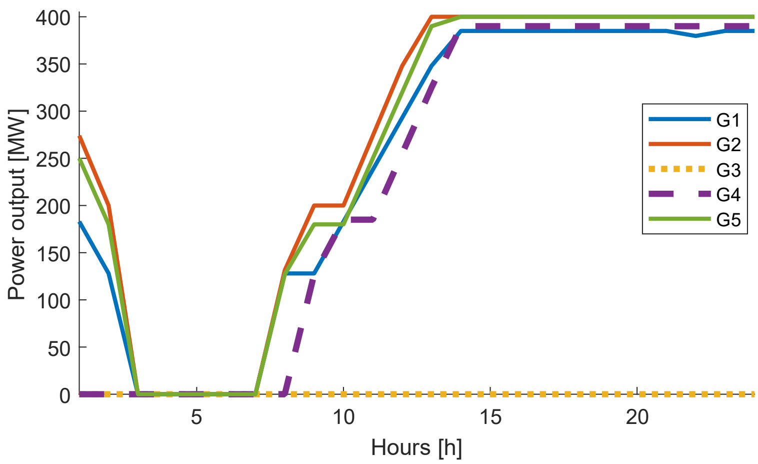
G4 and therefore the optimizer decides to generate with G4 instead. However, even if taxes are kept as the original case A (4.00%), keeping all other variables constant, and assuming that the optimization model obtains the same production profile for either G3 or G4 (an assumption that is not realistic, but is useful for analyzing the impact of modeling the income tax) a price increase could cause the same change from generating with G3 to doing it with G4. For the specific case that is being analyzed, the turning point where the expense of generating with G4 would be cheaper than using G3 is when the price increases by 11.48%, as shown in case C.

4.3.4 Individual income model for different levels of detail

As previously mentioned in Section 4.3.2 Income curve vs. individual income with 100% ownership and equal taxes for all generators, the proposed formulation implies a higher computational burden than the classical version. For this reason, four cases have been run to analyze them in detail, and determine the convenience of discretizing with greater or lesser precision taking into account the size of the resulting problem, the execution



(a) 4.0 % tax for generation unit G3.



(b) 4.5 % tax for generation unit G3.

Figure 4.7: Generation of the units for the 0.05 € discretization step case and different taxes.

time and the level of detail obtained. Results for different discretization steps are shown in Table 4.6.

From these four cases, the discretization with a step of 0.05€ seems to be the most appropriate, since it reduces the execution time by an order of magnitude compared to 0.01€, and the difference in schedule is minimal. Additionally, Figure 4.8 presents in a graphical manner 100 cases with different discretizations, starting at 0.01€ and increasing the step size by 0.01€ until 1€. It can be appreciated that the time decreases exponentially, whereas the decrease in profits and the increase in error are more linear.

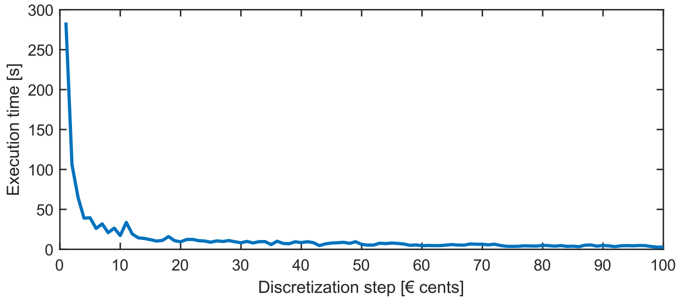
Table 4.6: Cases with different discretization steps.

	Individual income			
Problem characteristics				
Discretization step [€]	0.01	0.05	0.10	0.50
Continuous var. no.	126230	25985	13455	3440
Binary var. no.	25793	5744	3238	1235
Resolution Time [s]	276.6	37.2	14.6	6.7
OPTCR [%]	0.01	0.00	0.00	0.00
Optimized results				
Energy sold [GWh]	23.93	23.93	23.91	24.30
Income [k€]	1383.22	1383.09	1382.19	1401.35
Taxes [k€]	270.26	270.21	270.00	273.77
Cost [k€]	1020.75	1020.58	1019.78	1033.63
Profits [k€]	92.22	92.30	92.41	93.95
Ex-post results				
Income [k€]	1383.20	1382.94	1381.65	1398.87
Taxes [k€]	270.26	270.21	269.98	273.65
Cost [k€]	1020.75	1020.58	1019.78	1033.63
Profits [k€]	92.20	92.16	91.89	91.59

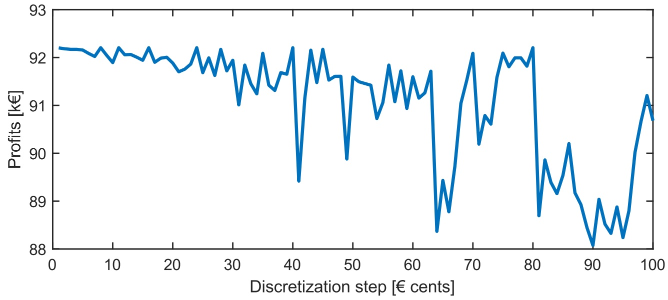
4.3.5 Stochastic case

In the previous analysis, a deterministic version of the formulation has been used to make it easier to analyze the advantages of the proposed modeling approach. However, the formulation presented in Section 4.2.1 Proposed formulation can account for 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 units power outputs and the associated costs, taxes and incomes. 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 4.7.

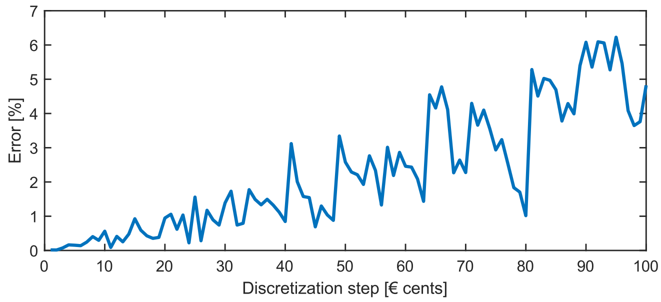
Figure 4.9 shows the generation profiles of units G3 and G4 for all nine scenarios. It can be seen that G3 is on 16 hours -although with different load levels according to the scenarios- whereas G4 remains off the whole day. As explained in Section 4.3.3 Income curve vs. individual income with <100% ownership and different taxes for the generators, unit G3 is cheaper in most scenarios due to the tax scheme. Only in the scenario with the highest price (12>11.48€/MWh) the taxes change the expense enough to make it more efficient to use G4. Therefore, as this is a common decision for all scenarios, G4 remains off, and the units' commitment are not changed.



(a) Execution time.



(b) Profits.



(c) Error: difference between optimized and expost profits.

Figure 4.8: Model performance according to discretization step.

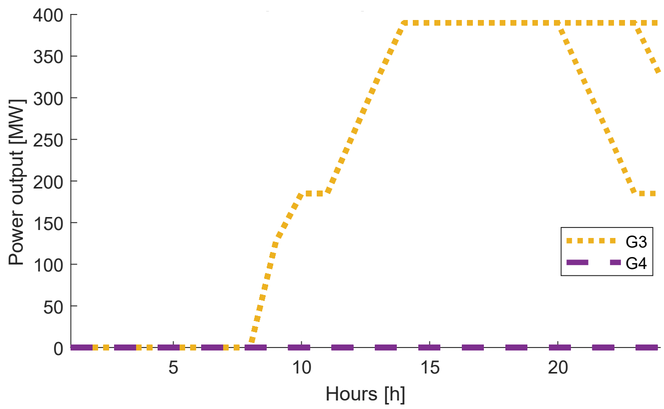


Figure 4.9: Power generation of units G3 and G4 for all scenarios.

Table 4.7: Expected values for the stochastic solution.

	Individual income
Problem characteristics	
Discretization step [€]	0.05
Continuous var. no.	99712
Binary var. no.	19107
Resolution Time [s]	12600
OPTCR [%]	2.06
Optimized results	
Energy sold [GWh]	23.73
Income [k€]	1374.56
Taxes [k€]	268.37
Cost [k€]	1013.53
Profits [k€]	92.66
Ex-post results	
Income [k€]	1374.39
Taxes [k€]	268.37
Cost [k€]	1013.53
Profits [k€]	92.49

4.4 Conclusion

The main conclusion that can be drawn from this chapter is the importance of representing in an accurate manner the different taxes that affect the units' operation and the incomes obtained by the generators with shared ownership. Both issues are quite common in many real systems, and as previously introduced in Section 2.4.2 Drawbacks of the formulation based on income functions, neglecting them can lead to very inaccurate results. In this chapter, a deterministic model has been first used to illustrate this finding, supported by several examples. In addition, a detailed stochastic optimization model is presented where the individual market income of each generator is modeled using the binary expansion technique. This approach 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. The study case presented shows its application to a realistic setting with satisfactory results, where the proposed model obtains results that are an order of magnitude more accurate than those obtained with the income curve alternative.

Chapter 5

Introduction of regulatory criteria in the self-UC model

The developments presented in this chapter are reflected in the working paper *"Introduction of regulatory criteria in the self-UC model"*, (Otaola-Arca & García-González, 2022).

5.1 Introduction

The liberalization of the electricity sector is based on the premise that it is possible to achieve the social optimum by replacing the centralized planning and operation by introducing competition among involved agents and the creation of electricity markets (Adib & Hurlbut, 2008). In particular, whereas transmission and distribution activities are natural monopolies that make them regulated activities, generation and retailing activities can be carried out under a competitive regime.

There are two main challenges that Generation Companies (GenCos) have to face when operating in a market environment. The first challenge is that they must prepare and submit bids for their generation portfolio following the applicable regulation. Such regulation depends on the market, and there is great variety among countries –this thesis is developed under a scheme similar to how markets have been designed in Europe: daily market clearing with uniform prices in each region (regional prices)–. The second challenge is that the decentralization of decision-making forces the companies to plan the operation of their own power plants. For instance, they have to decide when to start up or shutdown their units.

The question that arises is how to guide the GenCos's decision-making process to plan the optimal operation of its generation assets. As in any other market, the idea that a rational agent will try to maximize a certain utility function is recurrent in the technical literature. For the case of a GenCo, such a utility function can be defined as the difference between its market revenues minus its generation expenses. Additionally, the possible uncertainty could be considered by introducing concepts of expected profit or adding some risk measures. This profit maximization approach would be consistent with the notion of the *invisible hand* (Smith, 1776), where it is assumed that the interaction of all competing agents will eventually lead to the same solution as in a centralized operation. This theory assumes the presence of at least a certain number of competing agents (perfect competition) which may not be the case. Therefore, the benefits of such an *invisible hand* do not always impose themselves, and the *visible hand* of the State may be necessary for this *system of natural freedom* to work. Since then, this assertion has been implemented in countries using the capitalist economy, with the United States of America (USA) as one of its references. No other country with a liberalized economy could show such an abundance of legislation aimed at limiting free competition's disruption. USA's first act outlawing monopolistic business practices dates back to 1890 (USA Congress, 1890).

As a consequence of these regulations, there are specific rules that market participants must respect in their daily activities. For example, in Spain, Law 24/2013 (Jefatura del Estado, 2013) states that agents must reflect their generation expenses in their bids. Given the complexity of the electricity system (diversity of technologies, discrete decisions such as group start-ups, technical constraints, fuel markets, and regulation of related systems such as the gas market), calculating such generation costs is not a simple task. However, there are references for the minimum and maximum values for the costs that a regulator could assume as acceptable. Therefore, when the regulator sees indications of underbids or overbids according to such values, it may initiate disciplinary proceedings and assess the situation in detail.

All the developments in the thesis try to formulate aspects of the units' operation that affect their expenses in a realistic manner. However, in both Chapter 3 and Chapter 4, it is assumed that whether the companies are price-taker or price-maker, they will try to maximize their profit as this is the conceptual academic framework used to study the expected behavior of the agents participating in an electricity market (Ventosa et al., 2005). However, since GenCos are obliged to reflect their expenses in the bids, the market-clearing would be equivalent to perfect competition where the net social welfare is maximized. Consequently, in the hypothetical case of a price-maker, a profit maximization model could provide results with strategic behaviors that deviate from the expected market outcome. Hence, the model would lose its function of providing correct planning according to what is most likely to happen in reality.

In this context, the company faces the dilemma of deciding what kind of optimization model should be used to plan the short term operation:

- A profit maximization model that implicitly considers the possible impact on market prices based on residual demand curves that aggregate the expected behavior of its competitors.
- A traditional Unit Commitment (UC) model that maximizes the net social welfare using the detailed data regarding the GenCo's units and partial information from its competitors and the demand.

This chapter attempts to provide the tools to answer to this dilemma by modeling both alternatives and proposing additional constraints to align the results of the models to the expected market outcome operating in a competitive manner.

The rest of the chapter is organized as follows:

- Section 5.2 Centralized vs. liberalized planning presents the centralized operation and liberalized market environments.
- Section 5.3 GenCos' competitive planning discuses the two alternatives to perform competitive optimization planing from the perspective of a GenCo, and presents the proposed optimization models.
- Section 5.4 Case Study shows how the models would operate for two extreme situations where a GenCo could have strong incentives to behave strategically.
- Section 5.5 Conclusion presents the main conclusions.

5.2 Centralized vs. liberalized planning

Centralized management of the electricity system was the norm in the past. Progressively, different countries have been liberalizing the sector by creating markets in which independent agents can participate. The following two subsections explain how a centralized operator or the GenCos are expected to behave while performing the operation planning for the two schemes.

5.2.1 Centralized: Social welfare maximization

In a centralized situation, the most optimal operation planning would be carried out by a diligent operator who knows the utility value of the demand and the generation expenses of all the power plants of the system. With all this data, he could propose an optimization model of the complete system which maximizes the demand utility minus generation costs (5.1). This objective, the maximization of utility of the demand minus the cost of the generation, is known as the social welfare maximization. To solve the maximization problem, equation (5.1) has to be differentiated and equaled to zero. Since the derivatives of the utility of the demand and the generation cost are the demand and supply functions, the problem would be solved as in (5.2).

$$\max\left[UtilityDemand(q) - GenerationCost(q)\right] \tag{5.1}$$

$$D(q) = S(q) \tag{5.2}$$

It is essential to highlight that, in order to carry out this optimization, such an operator should have the detailed information about the complete system, such as:

- Generation: detailed cost structure, technical constraints, and operation couplings among the units.
- Demand: utility of the demand considering that a part of it is inelastic, but there is also a portion of it that is price dependent (this second part is increasing).

5.2.2 Liberalized: Agents' profits maximization

In a liberalized market situation, decisions are not made centrally but rather by all the different agents managing their own portfolios. Therefore, as each one of the GenCos operating in the market must make its own decisions regarding the operation planning of its units, the objective of their optimization tools is not that of a centralized operator. On the one hand, GenCos would try to maximize their revenues in the market minus their generation expenses as in (5.3a). On the other hand, the demand would try to maximize its utility minus the cost of purchasing energy in the market as in (5.3b).

$$\max \left[Income(q) - GenerationCost(q) \right] \tag{5.3a}$$

$$\max \left[UtilityDemand(q) - Purchases(q) \right] \tag{5.3b}$$

How does the liberalized approach perform differently from the centralized option? The answer to that question depends on the level of competitiveness (Schweppe et al., 2013). On the one hand, in a perfectly competitive market with low entry barriers and many agents participating in it without any dominant player, there will be no market power, and it will perform similarly to the centralized approach. On the other hand, if there is an oligopolistic situation where there are agents with the ability to influence the market, there is the possibility that they behave strategically deviating the market functioning from that of perfect competition.

5.2.2.1 Perfect competition case

In a market with perfect competition, equations in (5.3) are replaced by (5.4) where the $Income(q)$ and $Purchases(q)$ terms have been particularized as the quantity times the market price. The ideal competition situation implies the agents have no market power, and therefore the price term is independent of their operation.

$$\max \left[MarketPrice \cdot q - GenerationCost(q) \right] \tag{5.4a}$$

$$\max\left[UtilityDemand(q) - MarketPrice \cdot q\right] \tag{5.4b}$$

To solve the maximization problem the equations in (5.4) are differentiated with respect to the power and equaled to zero. In a perfect competition environment, neither the demand nor the GenCos have the market power to affect the price. Therefore, as the price does not depend on q, the derivative of $Markeprice \cdot q$ is equal to $Marketprice$ as in (5.5).

$$MarketPrice - GenerationCost'(q) = 0 \tag{5.5a}$$

$$UtilityDemand'(q) - MarketPrice = 0 \tag{5.5b}$$

$$UtilityDemand'(q) - GenerationCost'(q) = 0 \tag{5.6}$$

If both (5.5) expressions are added together, the price term is canceled and (5.6) is obtained. That equation is the same as the one obtained when solving (5.1) by deriving and equaling to zero. This results in the idea of clearing the market as the intersection of the demand and supply functions that, in the perfect competition case, will reflect the marginal utility of the demand and the marginal cost functions, respectively.

5.2.2.2 Imperfect competition case

In this case, there might be agents with the theoretical capability to exercise market power. This price is not unrelated of their behavior (generation decisions). Therefore, as the price is dependent on q (5.7), when solving the maximization problem, the derivative of $MarketPrice(q) \cdot q$ is not equal to $MarketPrice$, so it does not lead to the same expression as in the perfect competition case.

$$\max\left[MarketPrice(q) \cdot q - GenerationCost(q)\right] \tag{5.7a}$$

$$\max\left[UtilityDemand(q) - MarketPrice(q) \cdot q\right] \tag{5.7b}$$

The existence of imperfect markets has been widely studied in the literature. In the case of the electricity sector, it has been the subject of many analyses (Adib & Hurlbut, 2008), which is why one of the critical points in the electricity sector regulation has been limiting the market power the different players could exercise. The two main practices discussed in this chapter are:

- Production withholding to increase the market price.
- Generating energy below cost to decrease the market price.

For these two behaviors, two basic conceptual examples are presented to illustrate in which situations there may be an incentive for them to occur.

A) Generating energy below cost

An example where a pure selfish optimizer may be interested in lowering the market price is when a company (C) buys more energy than it sells. The energy it sells is what the generation part of the company produces, and the energy it buys is that which the retail part of the company sells to end customers. To understand this better, the following example is presented:

- Generation
  - Other firms
    - 300MWh 40€/MWh
    - 300MWh 50€/MWh
    - 300MWh 60€/MWh
  - Company C
    - 300MWh
- Demand
  - Other firms
    - 400MWh 100€/MWh
  - Company C
    - 400MWh 100€/MWh

In Figure 5.1, the supply curve of the competition firms with the three steps corresponding to the three generation units is plotted; the demand curve that includes both the demand of the competition and the retailer of company C; and the residual demand curve faced by the generating of company C.

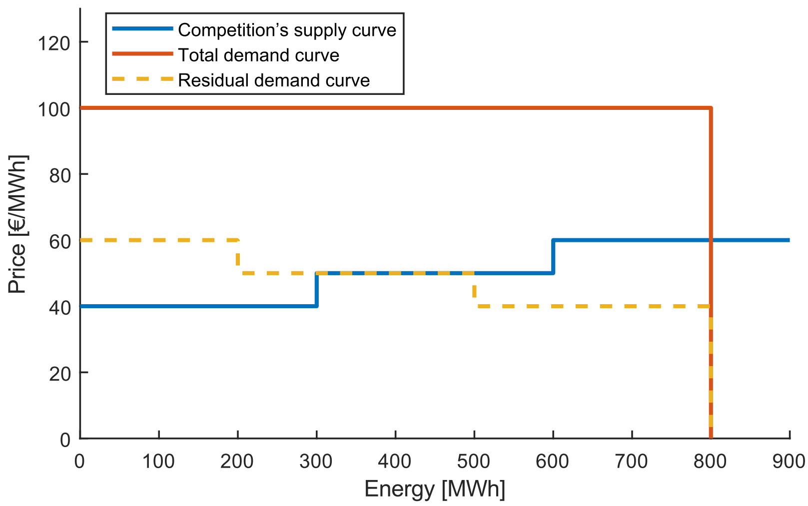


Figure 5.1: Energy purchases.

For simplicity, let us assume that the optimizer must decide whether or not to connect the C's 300MW generator, and if it does, it must produce at the maximum power output. Therefore, there are two possible cases:

a) The optimizer does not connect C's generator: The market price is 60€/MWh, the generation revenues are $0 \cdot 60 = 0$€, and the retailer cost $400 \cdot 60 = 24000$€. Therefore, it has a total cost of 24k€.

b) The optimizer connects C's generator: The market price is 50€/MWh, the generation revenues are $300 \cdot 50 = 15000$€, and the retailer cost is $400 \cdot 50 = 20000$€. Therefore, it has a total cost of 5k€ plus the generation cost.

The cost seen by the optimization algorithm is reduced by 19k€ in case b) compared to case a). For that reason, as long as the generation costs are less than that, it will be profitable to produce energy. The variable cost for which it is profitable would be $19000/300 = 63.33$€/MWh, which is higher than the market price. Due to the joint optimization of the generation and retail parts of company C, the combined revenue would be higher producing energy with up to 13.33€/MWh in generation losses than not incurring generation losses and having a higher market price.

What would happen in a context with centralized management whose objective was to maximize social welfare? It has just been demonstrated that company C makes more profits with a generation cost of up to 63.33€/MWh. If, for example, that generation cost was 62€/MWh, the unit would be represented in the far right part of the curve and should not produce. The calculation of the maximization of the social welfare would result in the following:

a) Social welfare without using C's generator: $100 \cdot 800 - 40 \cdot 300 - 50 \cdot 300 - 60 \cdot 200 = 41000$€.

b) Social welfare using C's generator: $100 \cdot 800 - 40 \cdot 300 - 50 \cdot 300 - 62 \cdot 200 = 40600$€.

Using C's generator implies a decrease in social welfare of 400€.

B) Production withholding

A case where an optimizer may be interested in raising the market price is when a company (C) has a large amount of low-cost generation and some generation unit G with a cost slightly below the marginal price that would result in the market. If the optimizer were to sell G's energy, that unit would have a minimal profit because its cost would be very close to the price at which it sells. However, the market price would decrease, and with it, the remuneration of the rest of C's generation. To better understand this situation, let us use an example similar to the one in the previous section:

- Generation
  - Other firms
    - 300MWh 40€/MWh
    - 300MWh 50€/MWh
    - 300MWh 60€/MWh
  - Company C
    - 190MWh 40€/MWh
    - 110MWh 49€/MWh (unit G)
- Demand
  - Other firms
    - 800MWh 100€/MWh

Figure 5.1 would still be valid for this case as the only curve that has changes is the demand curve, but now we supposed company C has no demand and the competitors have 800MWh.

For simplicity, let us assume that the optimizer must decide whether or not to connect C's generators, and if it does, they must produce at the maximum power output. The four possible cases are the following:

a) The optimizer does not connect any of C's generators: The market price is 60€/MWh, the generation revenues are $0 \cdot 60 = 0$€, and the generation cost are $0 \cdot 40 + 0 \cdot 49 = 0$€. Therefore the profits are 0€.

b) The optimizer connects the C's 190MW generator: The market price is 60€/MWh, the generation revenues are $190 \cdot 60 = 11400$€, and the generation cost are $190 \cdot 40 + 0 \cdot 49 = 7600$€. Therefore the profits are 3800€.

c) The optimizer connects the C's 110MW generator: The market price is 60€/MWh, the generation revenues are $110 \cdot 60 = 6600$€, and the generation cost are $0 \cdot 40 + 110 \cdot 49 = 5390$€. Therefore the profits are 1210€.

d) The optimizer connects both C's generators: The market price is 50€/MWh, the generation revenues are $300 \cdot 50 = 15000$€, and the generation cost are $190 \cdot 40 + 110 \cdot 49 = 12990$€. Therefore the profits are 2010€.

With these results, a profit maximization at the portfolio level would choose solution b). The optimizer is able to detect that the profits obtained by the 110MW generator (inframarginal unit G) when the 190MW generator is already connected are lower than the decrease in revenues caused to that unit by the market price reduction. However, since option d) is individually profitable for both generators, this is the option that the optimizer should choose.

In this case, if we were to consider a centralized approach, both C's units would be in the left zone of the market-clearing price, and the therefore they should be generating a total of 300MWh. The calculations regarding the social welfare are the following:

a) Social welfare using both C's generators: $100 \cdot 800 - 40 \cdot 300 - 40 \cdot 190 - 49 \cdot 110 - 50 \cdot 200 = 45010$€.

b) Social welfare using one of C's generators: $100 \cdot 800 - 40 \cdot 300 - 40 \cdot 190 - 50 \cdot 300 - 60 \cdot 10 = 44800$€.

Using just one of C's generator implies a decrease in social welfare of 210€.

5.3 GenCos' competitive planning

A consequence of the market liberalization is the decentralization of the decision-making process. GenCos are obliged to plan the operation of their own generation plants. For this planning task, they resort to the use of optimization models to maximize their profits. However, it is crucial to keep in mind that the accuracy of these models must be as high as possible. Otherwise, their results will not represent the actual outcome of the market and, therefore, will not be valuable tools in the company's decision-making. Consequently, they need to account for all the rules that could condition the behavior of market participants.

The application of a pure theoretical profit-maximization model could lead to the exercise of market power. Therefore, this results would not be realistic as the GenCo has to reflect in its offers the real expenses of its generation units. Within this framework, in this thesis we propose three models so that the GenCo can select the one that better fits its needs depending on the regulation in force, or as tools that could be used just for theoretical analysis not necessarily leading to a real behavior in the market. In addition, these models are also valuable tool to be used by the regulator authorities in charge of monitoring the market performance to carry out theoretical analysis of the GenCos' expected behaviors. The proposed models are the following:

- *Pure profit maximization model*: This model is detailed in Chapter 4 Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology and therefore it is omitted in the rest of the chapter. This model should not be used by agents who participate in markets where there are rules that strictly limit their behavior.
- *Regulatory-constrained profit maximization model*: The main idea is to take advantage of all the profit-maximization models that have been published in the literature, but adding a set of constraints intended to limit the strategic behaviors presented in Section 5.2.2.2 Imperfect competition case to obtain competitive solutions. This model is presented in Section 5.3.1 Regulatory-constrained profit maximization model hereafter.
- *Social Welfare equivalent optimization model*: In a market environment there is not a central planner in charge of finding the optimal operation of all the generation system. However, a GenCo could try to emulate what such central planner would do taking as input data the available information published by the market operator, i.e. the generation offers and buy bids that should reflect the generation expenses of the competitor GenCos and the utility of the demand. Such data are also used in the other two models for the price impact representation; however, they are critical in this model as without the information regarding the rest of the generation and demand, it is impossible to model the maximization of the social welfare. This model is presented in Section 5.3.2 Social Welfare equivalent optimization model.

5.3.1 Regulatory-constrained profit maximization model

This *regulatory-constrained model profit maximization model* consists of the addition of the constraints presented in this section to the *pure profit maximization model* explained in Section 4.2.1 Proposed formulation. All the equations from that previous model need to be used, including the objective function.

The equations proposed ensure the correct behavior of the generating units at the cost of increasing the computational load. To ensure that this increase is not excessive, the first measure that should be taken is to limit the application of the constraints to those generating units that are considered likely to cause problems. For that matter, G^{ind} is defined as a subset of the set of all the units G. For instance, plants such as nuclear power plants (whose generation is usually known and, in most cases, fixed), renewable generation, and in general low-cost generation should not be included in G^{ind}. Instead, G^{ind} should consist of those units that are susceptible to being left uncommitted or committed under cost, in general, those whose costs are closer to what may be the marginal generation unit.

The following two subsections present the additional constraints that should be included in the model to obtain competitive results preventing generation below cost and generation withholding.

5.3.1.1 Non-negative individual income case

This situation occurs when any generation unit incurs in individual losses; that is, its generation expenses are greater than its profits. Thanks to the development presented in Chapter 4 based on the binary expansion technique that allows modeling the individual market income of each unit, it is sufficient to apply equation (5.8) to ensure that the sum of hourly revenues must be greater than the sum of hourly expenses throughout the day. Using the constraint with the set of hours of the day instead of every hour independently is because certain hours can lose money. For example, the initial hour where the start-up cost is incurred would have negative profits. Another example could be some single hour in which the generator loses money but still earns more being committed than turning off and on again in a very short period. This is something that the regulator would accept in principle, and in fact, complex bids such as declaring a minimum income condition are designed to ensure that agents can recover their cost when facing non-convex functions such as discrete commitment and start-up costs.

$$\sum_{\substack{t \in T \\ Hmin_g^{sd} < t}} [incG_{g,t}] \geq \sum_{\substack{t \in T \\ Hmin_g^{sd} < t}} [csG_{g,t} + txG_{g,t}] \qquad \forall g \in G^{ind}, d \in D \tag{5.8}$$

$$Hmin_g^{sd} = \begin{cases} TSD_g \cdot IS_g + IP_g/RD_g \\ \qquad if\ TmnOn_g \leq TUo_g - IP_g/RD_g \\ TSD_g \cdot IS_g + IP_g/RD_g + TmnOn_g - TUo_g - IP_g/RD_g \\ \qquad if\ TmnOn_g > TUo_g - IP_g/RD_g \end{cases}$$

Parameter $Hmin_g^{sd}$ is critical for the problem to be feasible. Its function is to exclude the first optimization hours if the unit was on before the start of the optimization horizon. The hours it excludes are the minimum hours that the unit needs to be on for its minimum on time and the shut down trajectory. If the term $Hmin_g^{sd}$ is not calculated correctly, this could lead to infeasibilities due to inconsistency between the ramp equations, and minimum "on" and "off" times, and equation (5.8).

5.3.1.2 Potential individual income case

In the case of generation withholding, the aim of the additional constraints is to force the units to be committed in cases where they could make profits individually. Unlike the previous case, there are no values for the revenue, cost and tax variables to compare. They do not exist precisely because the units would be off at the end of the optimization unless some additional constraints are imposed. Therefore, what is proposed in this thesis is to define a reference generation profile, determine whether it would be profitable to generate with that profile, and force the units' commitment during the most profitable hours. The formulation works as follows:

- Determine a feasible generation profile that is considered reasonable. The correct choice can be challenging and is highly subject to the knowledge of the professionals in charge of using the optimization tools. This profile must be determined before the optimization as it is an input data parameter.
- Calculate the maximum revenue that the unit could obtain in the market with that generation. All the possible alternatives are evaluated, i.e., starting the unit at hours 1, 2, 3, etc. It is essential to consider that the theoretical income obtained in each hour is computed as the corresponding generation of the profile times the market price that would result if such generation was actually produced.
- Finally, the maximum income that would be obtained in all these options is compared with the generation expenses, and if it is positive, the unit's commitment during the hours it would receive that maximum income is forced.

In order to conceptually explain the formulation, the following simplified example is defined:

- Optimization period: 4 hours.
- Residual demand curves: presented in Figure 5.2.
- Generation units: G={G1,G2}
- Generation units subject to commitment enforcing: G^{ind}={G1}
- Reference generation profile for unit G1: 100MWh one hour and 150MWh the following.
- The generation of G2 is supposed fixed at 200MWh each hour.

For this example, Figure 5.3a shows the possibilities to turn on G1 and Figure 5.3c displays the income that it would obtain for such operation. These incomes are calculated as the energy in Figure 5.3a times the price in Figure 5.3b. In this latter figure, it can be appreciated that the price when considering G1's energy is lower for the hours it is generating.

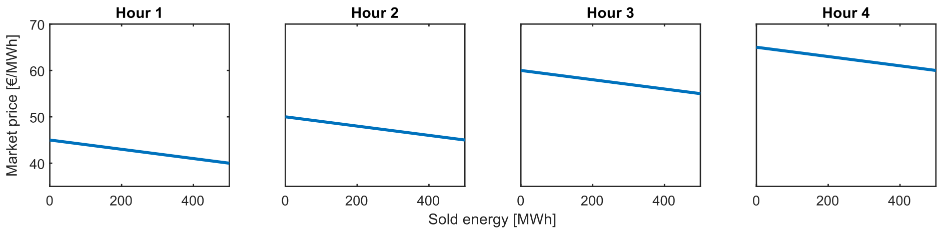
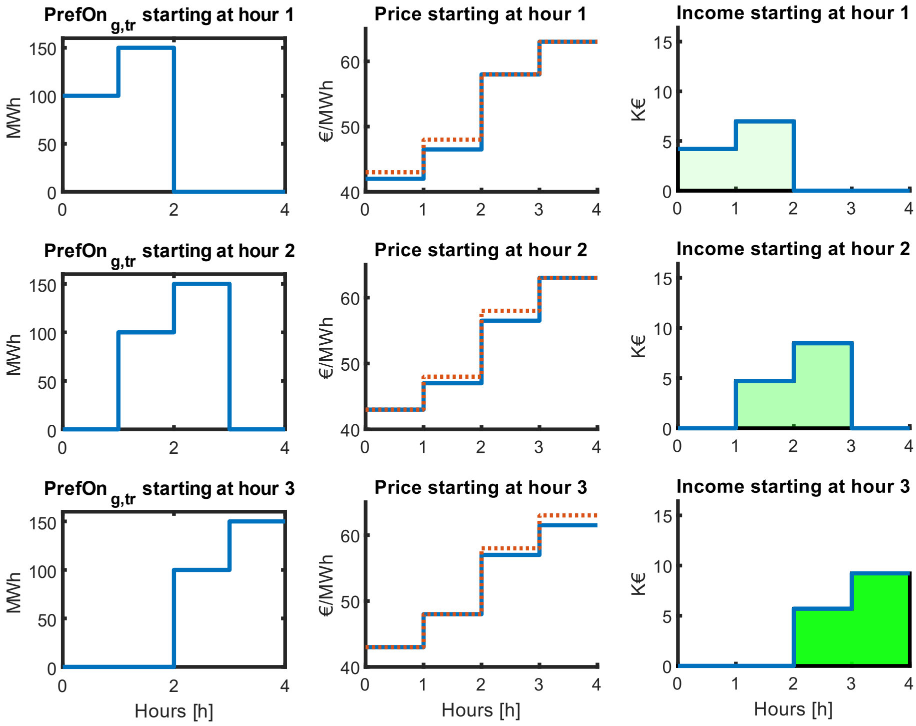


Figure 5.2: Residual demand curves for the 4 hours of the conceptual example.



(a) Possibilities in which the unit can be connected with the reference generation profile $PrefOn_{g,tr}$.

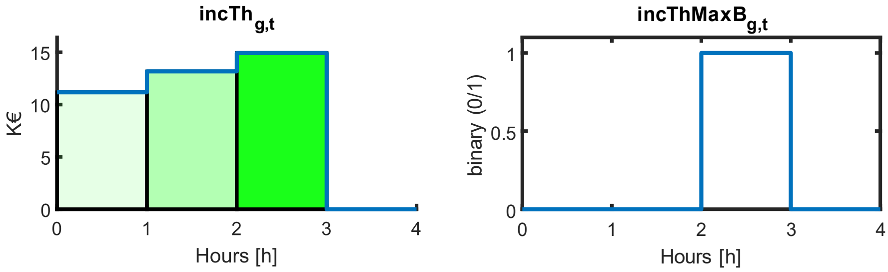
(b) Corresponding prices for each option. Price without unit G1 (dashed orange) and considering its reference profile (blue).

(c) Income for the different possibilities in which the unit can be connected with the reference generation profile $PrefOn_{g,tr}$.

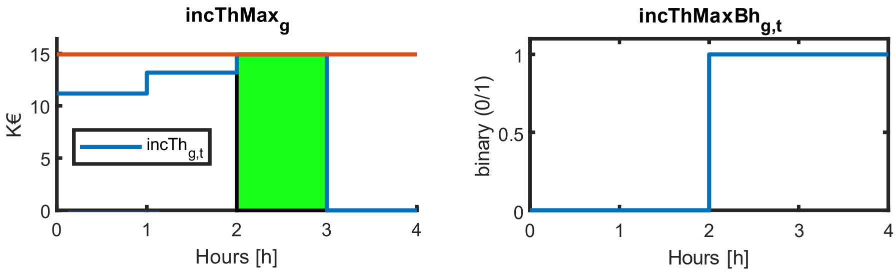
Figure 5.3: Income and market prices for the different alternatives in which the unit is being evaluated.

Figure 5.4a shows for each hour the total income that would be obtained if G1 was turned on that hour. The green areas in this figure correspond to those in Figure 5.3c. The maximum value for the income of the different options is calculated in Figure 5.4c. This maximum income corresponds to hour 3, which means that G1 would make the higher profits if it starts up at hour 3 and it is committed during hours 3 and 4. Figure 5.4b shows the binary variable corresponding to the startup hour, and Figure 5.4d shows the binary variables corresponding to the hours G1 has to be committed.

Finally, if the maximum income ($incThMax_g$) is higher than the generation cost



(a) Total income depending on the startup hour. (b) Startup hour for the maximum income.



(c) Maximum income. (d) Hours to be committed.

Figure 5.4: Main variables for the formulation.

($CSteo_g$, which includes the tax expenses), G1's commitment would be forced according to Figure 5.4d (during hours 3 and 4).

After explaining conceptually how the model works, the following is the complete formulation of the additional constraints to be included.

To improve the equation readability, we have defined values for some parameters and set elements in (5.9). They are not defined in the general nomenclature as they are just combinations of existing parameters or sets and used just to avoid repetitions:

- t'' is an element of T defined in (5.9a) according to set elements t and tr. It used in (5.9d) to compute a *big M* parameter, and in equations (5.10), (5.11), (5.12), and (5.13).
- $Hmax_g$ is used as a condition for the possible elements of t. It is used to exclude some hours at the end of the optimization horizon known beforehand to be hours in which the generation profile would not fit in the simulated time horizon. It is calculated in (5.9b) to be used in equations (5.10), (5.11), (5.12), (5.13), (5.14), (5.15), and (5.16).
- $Hmin_g^{su}$ is used as a condition for the possible elements of t. Depending on the initial conditions, it excludes some time periods at the beginning of the time horizon. It is calculated in (5.9c) to compute $MaxIncG_g$ in (5.9d) and in equations (5.10), (5.11), (5.12), (5.13), (5.14), (5.15), (5.16), (5.17), and (5.20).
- $MaxIncG_g$ acts as tight value for some *big M* constraints involving the market price. It is computed in (5.9d) to be used in equations (5.15) and (5.19). It is

calculated as the maximum of the cross correlation between the generation profile $PrefOn_{g,tr}$ and the maximum price of each hour of the day, for which the first points ($i = 1$) of the residual demand curves $RD\Pi^{E}_{i=1,t}$ are used.

$$t'' = t + tr - 1 \tag{5.9a}$$

$$Hmax_g = T - TrefOn_g + 1 \tag{5.9b}$$

$$Hmin^{su}_g = \begin{cases} TSU_g \cdot (1 - IS_g) & if\ TmnOff_g \leq TDo_g \\ TSU_g \cdot (1 - IS_g) + TmnOff_g - TDo_g & if\ TmnOff_g > TDo_g \end{cases} \tag{5.9c}$$

$$MaxIncG_g = \max_{t \in T} \left[\sum_{tr \in TR} \left[RD\Pi^{E}_{i=1,t''} \cdot PrefOn_{g,tr} \right] \right] \tag{5.9d}$$

To determine whether a generation unit would be profitable if it were committed, the first thing needed is the price that would result once it is connected. Therefore, when using the residual demand curves, it is necessary to consider the energy provided by all the connected units plus the one under analysis. As the analysis is performed using a reference generation profile with different power output for each hour, the theoretical prices that will result depend on both the unit g and the period tr of the reference profile to consider what would happen as it is turned on in the different hours. In addition to equations (4.4), (4.5) and (4.6) that are used to calculate the final price, equations (5.10), (5.11) and (5.12) are added to obtain the prices needed to evaluate each unit. In them, it is essential to note that the variable $a_{i,t}$ is replaced by the variable $a^{g}_{g,i,t,tr}$, which depends on g and tr, and that there is a relationship between the time sets t and tr using t''. In addition, the equations are not applied to all hours of the day as only those in which the whole reference profile is fully included in the optimization horizon are interesting.

$$\sum_{i \in \Omega^{i}_{t''}} \left[a^{g}_{g,i,t,tr} \right] = 1 \qquad \forall g \in G^{ind}, t \in T, tr \in TR, Hmin^{su}_g < t \leq Hmax_g \tag{5.10}$$

The total generation considered in (5.11) and (5.12) is the generation of all connected units except the unit analyzed ($g' \in G$, $g' \neq g$) plus the power of the reference profile of that unit $PrefOn_{g,tr}$.

$$\sum_{\substack{g' \in G \\ g' \neq g}} [pt_{g',t''}] + PrefOn_{g,tr} \geq \sum_{i \in \Omega^i_{t''}} \left[a^g_{g,i,t,tr} \cdot \underline{RDq}_{i,t''} \right]$$
$$\forall g \in G^{ind}, t \in T, Hmin^{su}_g < t \leq Hmax_g, tr \in TR \tag{5.11}$$

$$\sum_{\substack{g' \in G \\ g' \neq g}} [pt_{g',t''}] + PrefOn_{g,tr} \leq \sum_{i \in \Omega^i_{t''}} \left[a^g_{g,i,t,tr} \cdot \overline{RDq}_{i,t''} \right]$$
$$\forall g \in G^{ind}, t \in T, Hmin^{su}_g < t \leq Hmax_g, tr \in TR \tag{5.12}$$

Equation (5.13) calculates for each hour the total revenue that would be obtained by turning on the unit at that hour with the generation profile defined in the parameter $PrefOn_{g,tr}$.

$$incTh_{g,t} = \sum_{tr \in TR} \left[PrefOn_{g,tr} \sum_{i \in \Omega^i_{t''}} \left[RD\Pi^E_{i,t''} \cdot a^g_{g,i,t,tr} \right] \right] \cdot (1 - TxI_g)$$
$$\forall g \in G^{ind}, d \in D, t \in T, Hmin^{su}_g < t \leq Hmax_g \tag{5.13a}$$
$$incTh_{g,t} = 0$$
$$\forall g \in G^{ind}, d \in D, t \in T, (t \leq Hmin^{su}_g \vee Hmax_g < t) \tag{5.13b}$$

Equation (5.14) establishes that $incThMax_g$ is greater than $incTh_{g,t}$ and combined with (5.15), that ensures that they are equal for one hour at least (because (5.16) forces $incThMaxB_{g,t} = 1$ one hour each day), they make $incThMax_g$ the the maximum of $incTh_{g,t}$. Therefore $incThMax_g$ is the value that has to be compared with the cost of generating with the reference profile $CSteo_g$, and $incThMaxB_{g,t}$ is a binary variable whose value is 1 for the hour in which the units has to be turned on in order to receive $incThMax_g$.

$$incThMax_g \geq incTh_{g,t} \qquad \forall g \in G^{ind}, t \in T, Hmin^{su}_g < t \leq Hmax_g \tag{5.14}$$

$$incThMax_g - incTh_{g,t} \leq (1 - incThMaxB_{g,t}) \cdot MaxIncG_g$$
$$\forall g \in G^{ind}, t \in T, Hmin^{su}_g < t \leq Hmax_g, \tag{5.15}$$

$$\sum_{\substack{t \in T \\ Hmin_g^{su} < t \leq Hmax_g}} [incThMaxB_{g,t}] = 1 \qquad \forall g \in G^{ind} \tag{5.16}$$

Equation (5.17) forces binary variable $incThMaxBh_{g,t}$ to be 1 at least for the hour $incThMaxB_{g,t}$ is equal to 1 and the following $TrefOn_g - 1$ hours. Therefore $incThMaxBh_{g,t}$ represents the most profitable hours to be committed in case the commitment is enforced.

$$\sum_{\substack{t' \in T \\ t - TrefOn_g < t' \\ t' \leq t}} [incThMaxB_{g,t'}] \leq incThMaxBh_{g,t} \tag{5.17}$$

$$\forall g \in G^{ind}, t \in T, Hmin_g^{su} < t \tag{5.18}$$

The income $incThMax_g$ is compared with the cost $CSteo_g$ using a *big M* type constraint in (5.19), where the variable $forceOn_g$ is equal to 1 at least when the revenue of generating with the reference profile is higher than the cost.

$$incThMax_g - CSteo_g \leq forceOn_g \cdot MaxIncG_g \qquad \forall g \in G^{ind} \tag{5.19}$$

Equation (5.20) forces the commitment during the hours specified in $incThMaxBh_{g,t}$ when the potential revenue is higher than the cost ($incThMax_g > CSteo_g$).

$$incThMaxBh_{g,t} + forceOn_g - 1 \leq v_{g,t} \qquad \forall g \in G^{ind}, t \in T, Hmin_g^{su} < t \tag{5.20}$$

5.3.1.3 Possible simplifications

The computational burden of using a generation profile with different load levels is relatively high. To mitigate such a burden, certain simplifications could be made using reasonable assumptions regarding the generation profile used as reference (being not feasible) or prices without considering the price impact in detail. However, performing simplifications in the evaluation mechanism could lead to cases where the individual theoretical profits of the groups are positive, but the optimized program loses money. Therefore, the units would be forced to be connected and disconnected at the same time, leading to an infeasible solution. The following are the three main options:

- Simplification A: Instead of a feasible profile, use a profile with a constant load level (e.g., 85% of maximum power). The advantage of this method is that it greatly reduces the number of binary variables for calculating the maximum theoretical revenue. In each hour, the different price values would be one for the final solution plus one for each generation unit whose possible commitment is checked. That is simpler than the proposed formulation, which needed one value for the final solution plus one for each period of the reference profile of each unit. The drawback of with this option is that the generation profile might not feasible, and during the optimization, a different and feasible one will be obtained. As the profile is different, there is nothing to ensure that the units' profitability is not lower than expected. If the profitability reaches a negative value, the problem will become infeasible. The changes that would need to be made to the complete model to adopt this simplification are detailed hereafter.

Parameters $PrefOn_{g,tr}$ and $a^{g}_{g,i,t}$ no longer depend on tr and become $PrefOn_g$ and $a^{g}_{g,i,t}$. Equations (5.10), (5.11), (5.12), and (5.13) are substituted by (5.21), (5.22), (5.23), and (5.24).

$$\sum_{i\in\Omega^i_t}\left[a^g_{g,i,t}\right] = 1 \qquad \forall g \in G^{ind}, t \in T, Hmin^{su}_g < t \leq Hmax_g \tag{5.21}$$

$$\sum_{\substack{g'\in G\\ g'\neq g}}\left[pt_{g',t}\right] + PrefOn_g \geq \sum_{i\in\Omega^i_t}\left[a^g_{g,i,t}\cdot \underline{RDq}_{i,t}\right] \qquad \forall g \in G^{ind}, t \in T, Hmin^{su}_g < t \leq Hmax_g \tag{5.22}$$

$$\sum_{\substack{g'\in G\\ g'\neq g}}\left[pt_{g',t}\right] + PrefOn_g \leq \sum_{i\in\Omega^i_t}\left[a^g_{g,i,t}\cdot \overline{RDq}_{i,t}\right] \qquad \forall g \in G^{ind}, t \in T, Hmin^{su}_g < t \leq Hmax_g \tag{5.23}$$

$$incTh_{g,t} = PrefOn_g \sum_{\substack{tr\in TR\\ i\in\Omega^i_{t''}}}\left[RD\Pi^E_{i,t''}\cdot a^g_{g,i,t''}\right]\cdot(1-TxI_g) \qquad \forall g \in G^{ind}, d\in D, t \in T, Hmin^{su}_g < t \leq Hmax_g \tag{5.24a}$$

$$incTh_{g,t} = 0 \qquad \forall g \in G^{ind}, d\in D, t \in T, (t \leq Hmin^{su}_g \vee Hmax_g < t) \tag{5.24b}$$

- Simplification B: Make the comparison with the price calculated in the optimization instead of calculating what would be the price after turning on each group. This option would reduce the price values of each hour to one. This simplification can be applied with or without the previous one. The problem of infeasibility due to negative profits is slightly greater than in the previous case as the prices would differ more than those computed with an unfeasible generation profile.

This simplification uses $a_{i,t}$ instead of $a^{g}_{g,i,t}$. Equations (5.10), (5.11), and (5.12) are not longer used, and equation (5.13) is substituted by (5.25).

$$incTh_{g,t} = \sum_{tr \in TR} \left[PrefOn_{g,tr} \sum_{i \in \Omega^i_{t''}} \left[RD\Pi^E_{i,t''} \cdot a_{i,t''} \right] \right] \cdot (1 - TxI_g)$$

$$\forall g \in G^{ind}, d \in D, t \in T, Hmin^{su}_g < t \leq Hmax_g \tag{5.25a}$$

$$incTh_{g,t} = 0$$

$$\forall g \in G^{ind}, d \in D, t \in T, (t \leq Hmin^{su}_g \vee Hmax_g < t) \tag{5.25b}$$

- Simplification A+B: Applying simultaneously simplifications A and B increased the probability of having an infeasible solution. $PrefOn_{g,tr}$ do not depend on tr and become $PrefOn_g$ and $a_{i,t}$ instead of $a^g_{g,i,t}$. Equations (5.10), (5.11), and (5.12) are not longer used, and equation (5.13) is substituted by (5.26).

$$incTh_{g,t} = PrefOn_g \sum_{\substack{tr \in TR \\ i \in \Omega^i_{t''}}} \left[RD\Pi^E_{i,t''} \cdot a_{i,t''} \right] \cdot (1 - TxI_g)$$

$$\forall g \in G^{ind}, d \in D, t \in T, Hmin^{su}_g < t \leq Hmax_g \tag{5.26a}$$

$$incTh_{g,t} = 0$$

$$\forall g \in G^{ind}, d \in D, t \in T, (t \leq Hmin^{su}_g \vee Hmax_g < t) \tag{5.26b}$$

- Simplification C: Compare an average cost for the group with the average price for the day. If the cost is lower than the price, the unit's commitment is enforced either by providing the number of hours to be committed or the specific pre-specified hours (e.g., expected peak hours). This option is the simplest regarding the computational complexity, and regarding the possibility of becoming infeasible, there is a trade off regarding the tightness of the cost value. If the value is overestimated, the model will, not work properly in some cases, but is more likely to obtain a feasible solution.

  Equations (5.10), (5.11), (5.12), (5.13), (5.14), (5.16), (5.15), and (5.17) are no longer used, $incThMaxBh_{g,t}$ becomes an input data parameter, and $CSteo_g$ represents an averaged generation cost. In addition, equation (5.19) is substituted by (5.27).

$$\sum_{\substack{t \in T \\ i \in \Omega^i_t}} \left[\frac{RD\Pi^E_{i,t} \cdot a_{i,t}}{24} \right] - CSteo_g \leq forceOn_g \cdot \max_{t \in T} \left[RD\Pi^E_{i=1,t} \right]$$

$$\forall g \in G^{ind} \tag{5.27}$$

Table 5.1 qualitatively shows the complexity of the different options and the risk of obtaining infeasible solutions. The numbers do not represent the continuous and binary variables and constraints but instead an approximation (in a precise calculation some operations in the first and last hours of the day would be discounted) of the times that specific processes involving extra variables and constraints have to be carried out.

This type of behavior is not a common occurrence, so it cannot be said that any

Table 5.1: Qualitative evaluation of the complexity and the risk of infeasible solutions for the the proposed formulation and possible simplifications.

	Price values per hour	Calculations to determine most profitable hours	Infeasibility risk
Proposed	$1 + \sum_{g \in G^{ind}} [TrefOn_g]$	$\sum_{g \in G^{ind}} [1]$	○ ○ ○ ○
Simp. A	$1 + \sum_{g \in G^{ind}} [1]$	$\sum_{g \in G^{ind}} [1]$	● ○ ○ ○
Simp. B	1	$\sum_{g \in G^{ind}} [1]$	● ● ○ ○
Simp. A+B	1	$\sum_{g \in G^{ind}} [1]$	● ● ● ○
Simp. C	1	0	● ● ● ●

model that is not protected will fail. However, it sometimes happens (especially if the portfolio is extensive), so it is good to have a solution for it. Considering the added computational burden of this protection, an excellent way to proceed would be to start by running the model without including the additional constraints. Then check whether the solution meets the rules (such a check could be done with the equations themselves). Finally, reoptimize by including all the equations if the rules are not met. In this way, in most cases, no extra time would be needed, and in those cases where it would be necessary, some information could be used from the first execution. For example, certain commitment variables of the units that were generating energy during the day could be fixed (e.g., the most profitable hours when they were generating) and remove such units from the set to which the checks are applied (G^{ind}).

5.3.2 Social Welfare equivalent optimization model

In the previous section, we have seen how a pure profit maximization model can be adapted to still be helpful to produce competitive results preventing certain behaviors that go against what a centralized operator would do to maximize social welfare. The problem encountered by the profit maximization model is that its objective is not the same as that of the centralized operator. Therefore, the question arises about how an agent would behave if it tried to maximize social welfare on its own. That is, setting as the model objective function the maximization of social welfare, using as input data an expected behavior for demand and competitors, and having as decision variables only the ones regarding its units.

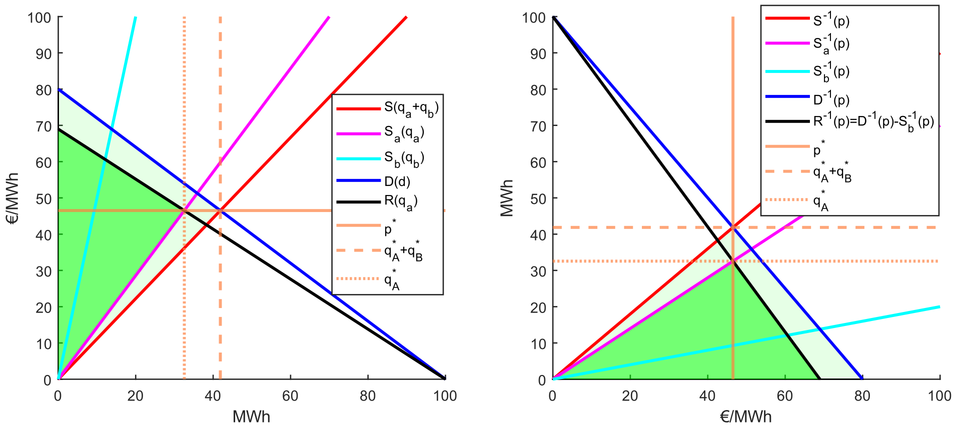
5.3.2.1 Model proposal

This section explains how a GenCo could adopt the centralized operator's objective of maximizing social welfare. Starting from the problem faced by such a centralized operator, we will see how to adapt it to the agent's perspective.

A) Idealized welfare maximization problem faced by a centralized operator.

A real social welfare maximization problem would be the one presented in (5.1), considering all the characteristics of the system in order to maximize the utility of the demand minus the cost of the generation. However, the actual cost functions of the generation units are complex. They have binary decisions and spatial and temporal linkages among the units. For this explanation we are going to use a stylized representation with ideal units with no minimum stable loads, no couplings between their operations, no time couplings, and that are represented just by a variable cost. A centralized operator who wants to maximize the social welfare would solve the problem as solving a market-clearing with only simple offers. It would create curves representing the utility of the demand (in the market, that is, to order the purchase bids in a descending manner) and the cost function of the system (sort the sale offers in an ascending way) and find the point where they intersect (market clearing). From the optimization point of view, this is equivalent to maximizing the area between the demand $D(q)$ and supply $S(q)$ curves (5.28), represented in light green in Figure 5.5a.

$$\max\left(\int_0^q [D(x) - S(x)]\,dx\right) \tag{5.28}$$



(a) Functions with respect to the generation (quantity) q.

(b) Inverse of the functions with respect to the price p.

Figure 5.5: Two approaches for social welfare maximization.

B) Residual demand equivalent to social welfare maximization.

Now we want to know if a GenCo could use the residual demand curve information to reach the point that maximizes the social welfare. That is, we want to know whether solving the problem expressed in (5.29) is equivalent to solve a proper welfare maximization as in (5.28).

$$\max\left(\int_0^{q_A} [R(x) - S_A(x)]\,dx\right) \tag{5.29}$$

In a system with only two companies, A and B, by definition, the inverse of the residual demand for company A (residual demand: $R_A(q_A)$) is the inverse of the demand function minus the supply function of all its competitors (5.30). And also by definition, the inverse of the supply function of the system is the sum of the inverses of the supply functions of all the GenCos (5.31).

$$R_A^{-1}(p) = D^{-1}(p) - S_B^{-1}(p) \tag{5.30}$$

$$S_T^{-1}(p) = S_A^{-1}(p) + S_B^{-1}(p) \tag{5.31}$$

From the solution of the centralized problem, we know that the optimum is obtained where the demand and total supply curves intersect. Therefore, for the optimum point, equations (5.32) and (5.33) are satisfied.

$$D(q_A^* + q_B^*) = S_T(q_A^* + q_B^*) \tag{5.32}$$

$$D^{-1}(p^*) = S_T^{-1}(p^*) \tag{5.33}$$

The maximization of the area between the residual demand and supply curves of A occurs where the curves intersect as with the maximization of the area between the demand and total supply of the system. Therefore, there is a point $[p^*, q_T^*]$ (where $q_T^* = q_A^* + q_B^*$) where the demand and total supply curves intersect, and another point $[p^{**}, q_A^{**}]$ where the residual demand intersects with the supply of A. To show that the maximization using the residual demand is equivalent to the maximization of the real social welfare, it suffices to demonstrate that $p^* = p^{**}$ and $q_A^* = q_A^{**}$. To check if this is true, we will start from the optimal point expressed in (5.33) and try to end up with $R_A^{-1}(p*) = S_A^{-1}(p*)$. Firstly we obtain (5.34) by replacing in (5.33), the inverse of the demand from (5.30).

$$R_A^{-1}(p*) + S_B^{-1}(p*) = S_T^{-1}(p^*) \tag{5.34}$$

The second step is to obtain (5.35) by replacing in (5.34) the inverse of the total supply from. (5.31)

$$R_A^{-1}(p*) + S_B^{-1}(p*) = S_A^{-1}(p*) + S_B^{-1}(p*) \tag{5.35}$$

Finally we cancel the term representing the inverse of the competitors supply and end up with (5.36), that was the intended objective. Thus it is shown that $p^* = p^{**}$ and $q_A^* = q_A^{**}$, and that the maximization of the area between the residual demand

and supply curves of the company A provides the values for p and q_A that would result in a direct social welfare maximization.

$$R_A^{-1}(p*) = S_A^{-1}(p*) \tag{5.36}$$

Figure 5.5 shows the different curves and maximization areas graphically for a simplified example, where it is intuitive that the maximization of both is equivalent.

C) From the idealized problem to the real world.

When going from an ideal case like the one presented, where even the demand and supply curves were linear as shown in Figure 5.5a, to a more realistic one like the one shown in Figure 5.6a, the exact process can be performed. On the one hand, a centralized operator would use all the demand and generation information to build the aggregated curves and maximize the green area between them. Note that the units of GenCo A are alternated with the rest of the generation units attending to their costs. On the other hand, A could use that demand and competition information to build a residual demand curve as represented in Figure 5.6b and then maximize the area between that residual demand curve and its own supply curve as in Figure 5.6c. Finally, such green area from Figure 5.6c can be decomposed into the black area under the residual demand curve (Figure 5.6d) and the magenta area under the GenCo's own supply curve (Figure 5.6b). That is precisely what allows going from the simplification to reality: A can replace the term of the objective function representing the magenta area with a term that accounts for its true costs, modeled with all the detail.

D) Applicability of the approach.

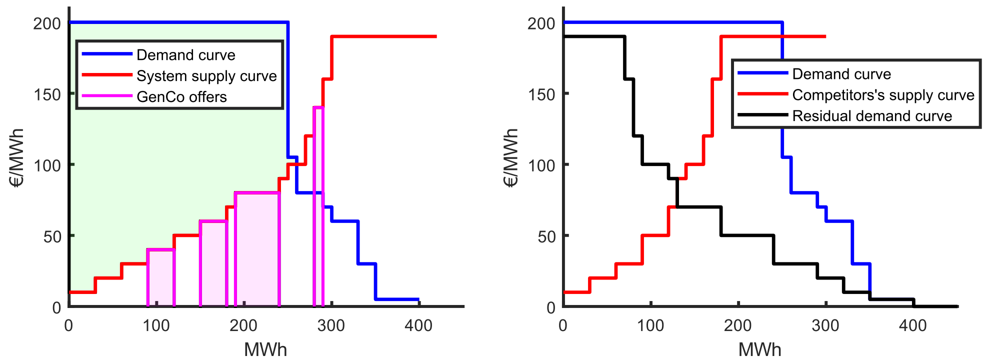
With this approach, a GenCo fulfills three objectives. First, it can solve a problem equivalent to the maximization of the system's social welfare. Second, the input data it needs are publicly available. In Spain, for example, the aggregate supply and demand curves are published every day, and the individual offers are available after three months. The company will have to make some residual demand curve prediction model, which is not trivial. However, the key is that the information for that prediction model is public information, unlike the information about all the technical and cost parameters of the competing generation units. Finally, the GenCo can consider the detailed technical and economic data regarding its own portfolio.

The resulting problem faced by the GenCo is presented in a schematic version in (5.37), where the area under the residual demand curve depends on the total energy produced, and the generation cost is a non-convex function. The actual equations are explained in the following section.

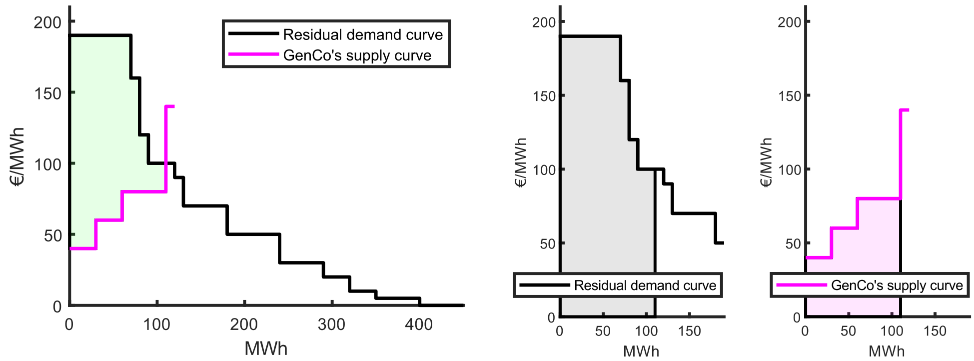
$$\max\left(ResidualDemandArea - GenerationCost - Taxes\right) \tag{5.37}$$

Subject to expenses calculation:

- Generation cost:



(a) System supply and demand. (b) Residual demand curve construction.



(c) Residual demand and GenCo's supply curve. (d) Area under the residual demand. (e) Area under the GenCo's supply.

Figure 5.6: Social welfare maximization example.

  - Operation and Maintenance (O&M): cost associated with the number of hours functioning and start-up maneuvers.
  - Fuel: the consumption is calculated according to power output and start-up and shut-down maneuvers.

- Taxes:
  - Fuel consumption.
  - Power generation.
  - Market income.
  - CO_2 emissions.

and technical constraints:

- Power limits: operation between maximum and minimum power output.
- Ramping limits: maximum variation in power output.
- Min time on/off: minimum time the units have to be on/off after a start-up/shut-down decision.
- Start-up type: type of start-up decisions according to the time the units have been down.
- Commitment coherence: relation between commitment status and start-up and shut-down decisions.

- Consumption: constraints regarding fuel consumption.

5.3.2.2 Mathematical formulation

This model requires the inclusion of the equations presented in this section plus the income curve modeling presented in Section 4.2.1 Proposed formulation (constraints (4.3), (4.4), (4.5), (4.6), (4.7), (4.8), (4.9), (4.10), (4.11), (4.12), (4.13), (4.14), (4.15), (4.16), (4.17), excluding the objective function (4.2)) and the general UC constrains presented in Appendix A.3 Unit Commitment technical constraints (equations: (A.9), (A.10), (A.11), (A.12), (A.13), (A.14), (A.15), (A.16), (A.17), and (A.18)).

The objective function in (5.38) maximizes the area under the residual demand curve minus the generation cost of the units $csG_{g,t}$. Such cost is computed with the equations in Section 4.2.1 Proposed formulation as already stated.

$$\max \left(\sum_{t \in T} \left[aRD_t - \sum_{g \in G} [csG_{g,t}] \right] \right) \tag{5.38}$$

In (5.39) the mentioned area under the residual demand curve is calculated as the sum of each price segment $RD\Pi^{E}_{i,t}$ times the power assigned to them $qRD_{i,t}$.

$$aRD_t = \sum_{i \in \Omega^i_t} \left[RD\Pi^{E}_{i,t} \cdot qRD_{i,t} \right] \qquad \forall t \in T \tag{5.39}$$

The total generation of the units must be equal to the total generation assigned to the segments of the residual demand curve as expressed in (5.40).

$$\sum_{g \in G} [pt_{g,t}] = \underline{RDq}_{i=1,t} + \sum_{i \in \Omega^i_t} [qRD_{i,t}] \qquad \forall t \in T \tag{5.40}$$

Finally, (5.41) ensures that $qRD_{i,t}$ is assigned to the residual demand segments in ascending order.

$$qRD_{i,t} \leq (\overline{RDq}_{i,t} - \underline{RDq}_{i,t}) \sum_{\substack{ii \in \Omega^i_t \\ ii \geq i}} [a_{ii,t}] \qquad \forall t \in T, i \in \Omega^i_t \tag{5.41}$$

5.3.2.3 Non-negative individual income

Observing the figures presented so far and considering the explanations of how the curves intersect, it can be intuited that when maximizing the social welfare (or the equivalent problem), all generation units have a cost lower than the market price. However, that only happens with idealized costs. When a detailed cost structure is considered, the optimal point for social welfare does not ensure that all units recover their operating costs. The non-convexities of the cost functions and the fact that it is the sum of the demand utility plus the generators' surplus that is maximized means that some generators may lose money if that has a higher impact on the demand utility.

If a GenCo were to produce energy at a loss, it could be accused of dumping. Therefore, what is likely to happen is that the GenCo's bids internalize its costs, its units are not cleared, and the actual market situation differs from the results obtained in the optimization. For this reason, although this model's objective is maximizing social welfare, it should be able to protect itself against the problem of programming units below cost. The solution for this problem would be the same as in the case of the profit maximization model. It would be sufficient to include in the model the equation (5.8), presented in Section 5.3.1.1 Non-negative individual income case.

5.4 Case Study

This section presents two different case studies analyzing how the proposed models produce competitive behaviors for extreme situations that create incentives for committing units that lose money (Section 5.4.1 Non-negative individual income case) and withhold generation by leaving units that could make profits uncommitted (Section 5.4.2 Potential individual income case).

In the first case, it is assumed that the company has a retail part that buys a fixed amount of energy at the price that results from the market clearing. In contrast, in the second case, it is assumed that the GenCo has a sizeable nuclear generation unit in its portfolio that has a fixed generation schedule throughout the whole day.

Situations in which an optimization model sees incentives to produce results with strong strategic behaviors may not be that common. In the two cases presented in this section, the data initially used in Chapter 4 Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology have been modified to force the occurrence of such behaviors to analyze how the proposed formulation would prevent them.

5.4.1 Non-negative individual income case

All the data used for this case study are online available in (Otaola-Arca, 2022c). The characteristics of the units are shown in Table 5.2, and CO_2 tax is $TxCO2 = 21$ €/ton. The residual demand curves are the ones used in Section 4.3 modified to increase the price decay per MWh by a factor of 2 and are displayed in Figure 5.7. Finally, the energy purchased by the retail part of the company is presented in Figure 5.8.

Three different executions were performed. The first execution, labeled in the figures as *No restrictions*, is the model presented in Section 4.2.1 Proposed formulation without any modification. The second execution, called *Non-negative profits*, is the same model but also including equation (5.8). Finally, the third execution refereed as *Social welfare*

Table 5.2: Generation units data. Non-negative individual income case.

Parameters	Units	G1	G2	G3	G4	G5	G6	G7
$\underline{P}_g$	[MW]	128.0	200.0	185.0	180.0	128.0	200.0	180.0
$\overline{P}_g$	[MW]	385.0	400.0	390.0	400.0	385.0	400.0	400.0
RU_g	[MW/h]	55.0	74.0	70.0	70.0	55.0	74.0	70.0
RD_g	[MW/h]	55.0	74.0	70.0	70.0	55.0	74.0	70.0
$TmnOn_g$	[h]	2	2	2	2	2	2	2
$TmnOff_g$	[h]	2	3	3	3	2	3	3
$PSU_{g,tu=1}$	[MW]	50.0	50.0	50.0	50.0	50.0	50.0	50.0
$PSU_{g,tu=2}$	[MW]	-	131.4	127.0	127.0	-	131.4	127.0
$PSD_{g,td=1}$	[MW]	0	0	0	0	0	0	0
TSU_g	[h]	1	2	2	2	1	2	2
TSD_g	[h]	1	1	1	1	1	1	1
IS_g	0,1	0	1	0	0	0	1	0
IP_g	[MW]	0	100	0	0	0	100	0
TUo_g	[h]	0	10	0	0	0	10	0
TDo_g	[h]	24	0	24	24	24	0	24
$TmnS_{g,su=1}$	[h]	2	3	3	3	2	3	3
$TmnS_{g,su=2}$	[h]	12	12	12	12	12	12	12
$TmnS_{g,su=3}$	[h]	24	24	24	24	24	24	24
$CNmn_g$	[$\mathrm{MWh_t}$/h]	304	435	450	445	304	435	445
$CNvr_g$	[$\mathrm{MWh_t}$/MWh]	1.59	1.30	1.60	1.50	1.67	1.37	1.58
$CNsu_{g,su=1}$	[$\mathrm{MWh_t}$]	537	549	572	558	537	549	558
$CNsu_{g,su=2}$	[$\mathrm{MWh_t}$]	726	729	675	747	726	729	747
$CNsu_{g,su=3}$	[$\mathrm{MWh_t}$]	1026	983	1076	1008	1026	983	1008
$CNsd_g$	[$\mathrm{MWh_t}$]	67.83	65.85	65.30	65.30	67.83	65.85	63.50
$CO2r_g$	[ton/$\mathrm{MWh_t}$]	0.19	0.19	0.19	0.19	0.19	0.19	0.19
$TxCN_g$	[€/$\mathrm{MWh_t}$]	2.50	2.50	2.50	2.50	2.50	2.50	2.50
TxE_g	[€/MWh]	1.00	1.00	1.00	1.00	1.00	1.00	1.00
TxI_g	[p.u.]	0.05	0.05	0.04	0.05	0.05	0.05	0.05
PCN_g	[€/$\mathrm{MWh_t}$]	20	20	20	20	20	20	20
Own_g	[p.u.]	1.00	0.90	1.00	1.00	1.00	1.00	1.00

is the model presented in Section 5.3.2.2 Mathematical formulation.

The resulting market price for the three models is displayed in Figure 5.9, whereas Table 5.3 shows the energy generated during each execution.

Table 5.3: Energy produced by each generation unit [MWh/day]. Non-negative individual income case.

Executions	G1	G2	G3	G4	G5	Total
No restrictions	5553	7175	5847	5553	6827	30955
Non-negative profits	6323	7175	0	0	6827	20325
Social welfare	5938	7975	0	0	7575	21489

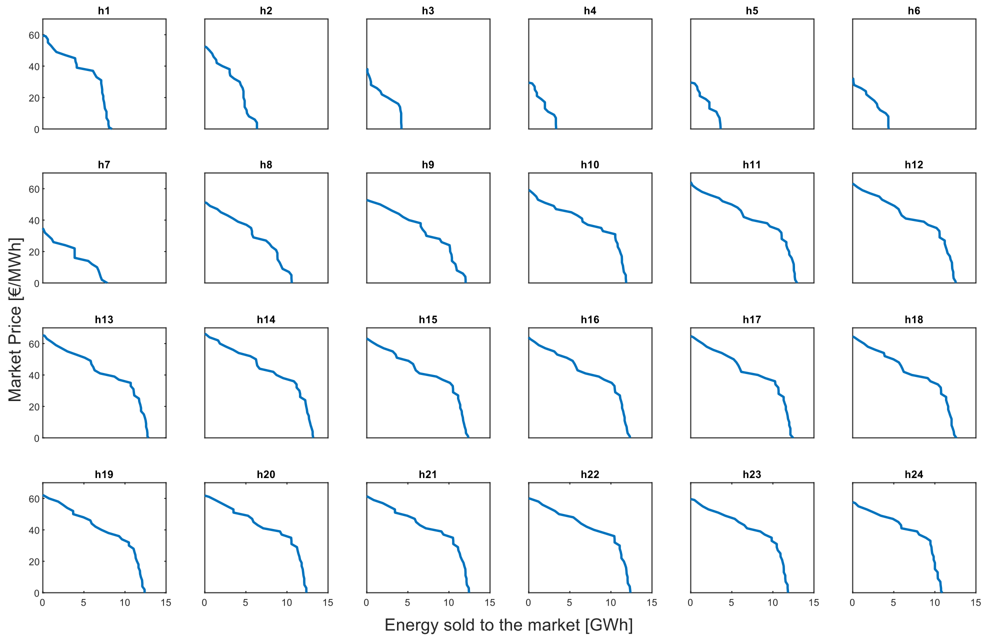


Figure 5.7: Modified residual demand curves for the 24 hours of the day. Non-negative individual income case.

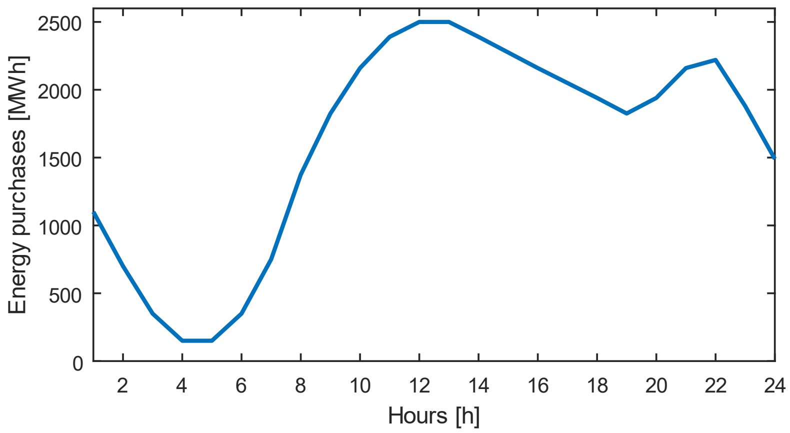


Figure 5.8: Energy purchases.

5.4.1.1 No restrictions vs Non-negative profits

In the first run, the optimizer prefers to connect units that individually lose money to lower the market price and thus pay less for the retail purchases. The individual profits of each generation unit are displayed in Figure 5.10, where it can be seen that units G1, G4 and G5 loose money.

In the second run, by imposing the constraint that individual profits cannot be negative, the optimizer disconnects units G4 and G5. Unit G1 is not disconnected because its generation becomes profitable as the market price rises by removing generation from

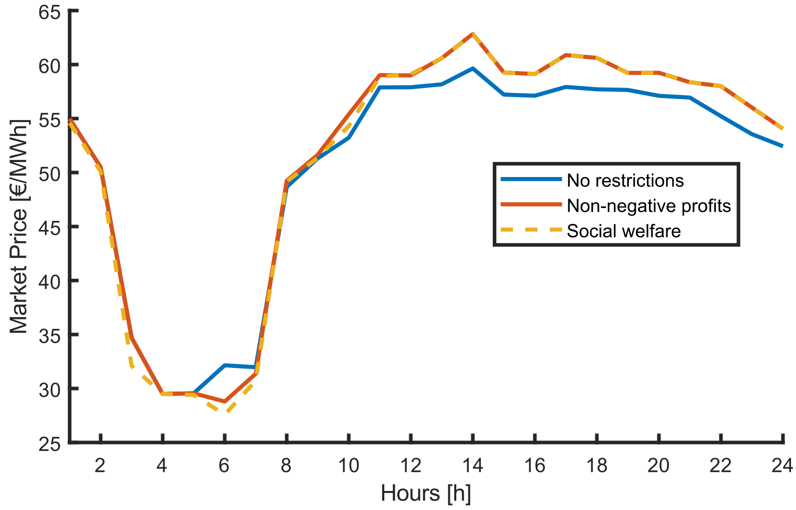


Figure 5.9: Market prices. Non-negative individual income case.

G4 and G5. In the same line, units G2 and G6, which were connected in the previous execution, increase their profits due to the higher price. Conversely, that price increase has a negative impact on the costs of the retail purchases. The units that are turned off (G4 and G5) stop losing 22.45k€, the units that remain committed earn 28.43k€ more, and the retail purchase cost increases by 67.42€. Therefore, the balance is that the operation is 16.54k€ worse.

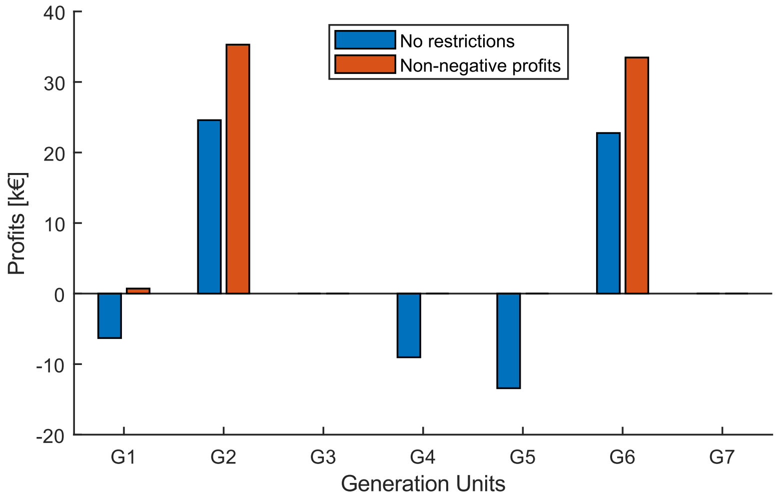


Figure 5.10: Income of each generator. Non-negative individual income case.

5.4.1.2 Non-negative profits vs. Social welfare

The *Social welfare* execution obtains a solution similar to the *Non-negative* alternative. The market situation used in this example creates an incentive for the GenCo to lower market prices, and the limit to that lowering is the operation costs of its units. That point is similar to the one sought by the objective function of the social welfare optimization, to find where the demand and supply functions intersect. That theoretical intersection occurs when the most expensive cleared unit makes neither profits nor losses. For the case the marginal unit cleared is not one of the GenCo's units, all the GenCo's generators that are cleared would make individual profits, as in this case. Therefore, in this situation both the *Regulatory-constrained profit maximization model* and the *Social Welfare equivalent optimization model* encounter the same limitation when trying to produce more energy and behave in a very similar manner.

5.4.2 Potential individual income case

All the data used for this case study are online available in (Otaola-Arca, 2022c). The characteristics of the units are shown in Table 5.4. The residual demand curves are the ones used in Section 4.3 but modified, and are displayed in Figure 5.11. The modification of the curves consists on increasing the price decay per MWh by a factor of 3, and multiply the obtained results by 1.4 to have prices that are not too low due to the increase in price decay. Finally, in addition to the five generation units shown in Table 5.4, there is a nuclear power plant (G6) that has a fixed generation of 1700MWh during the whole day. G6's generation is important regarding income, which depends on the total power generated; however, the cost parameters of G6 are not needed because the power output itself is not subject to optimization.

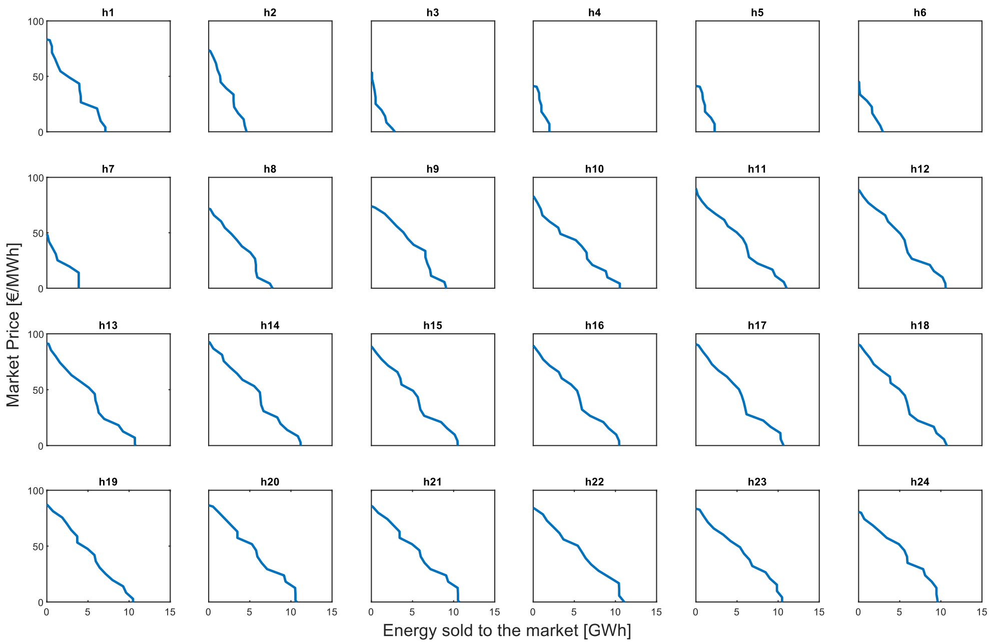


Figure 5.11: Modified residual demand curves for the 24 hours of the day. Potential individual income case.

For this case there were also three executions. The first one, identified as *No restrictions*, was again the model presented in Section 4.2.1 Proposed formulation but including equations (5.10), (5.11), (5.12), and (5.13). Those additional equations did

Table 5.4: Generation units data. Potential individual income case.

Parameters	Units	G1	G2	G3	G4	G5
$\underline{P}_g$	[MW]	128.0	200.0	180.0	128.0	200.0
$\overline{P}_g$	[MW]	385.0	400.0	400.0	385.0	400.0
RU_g	[MW/h]	140.0	190.0	170.0	150.0	180.0
RD_g	[MW/h]	140.0	190.0	170.0	150.0	180.0
$TmnOn_g$	[h]	2	2	2	2	2
$TmnOff_g$	[h]	2	3	3	2	3
$PSU_{g,tu=1}$	[MW]	50.0	50.0	50.0	50.0	50.0
$PSU_{g,tu=2}$	[MW]	-	131.4	127.0	-	131.4
$PSD_{g,td=1}$	[MW]	0.0	0.0	0.0	0.0	0.0
TSU_g	[h]	1	2	2	1	2
TSD_g	[h]	1	1	1	1	1
IS_g	0,1	0	0	1	0	0
IP_g	[MW]	0	0	100	0	0
TUo_g	[h]	0	0	10	0	0
TDo_g	[h]	24	24	0	24	24
$TmnS_{g,su=1}$	[h]	2	3	3	2	3
$TmnS_{g,su=2}$	[h]	12	12	12	12	12
$TmnS_{g,su=3}$	[h]	24	24	24	24	24
$CNmn_g$	[$\mathrm{MWh_t}$/h]	304	420	445	304	430
$CNvr_g$	[$\mathrm{MWh_t}$/MWh]	1.59	1.20	1.50	1.67	1.25
$CNsu_{g,su=1}$	[$\mathrm{MWh_t}$]	537	540	558	537	545
$CNsu_{g,su=2}$	[$\mathrm{MWh_t}$]	726	700	747	726	710
$CNsu_{g,su=3}$	[$\mathrm{MWh_t}$]	1129	1081	1109	1129	1081
$CNsd_g$	[$\mathrm{MWh_t}$]	67.83	65.85	63.50	67.83	65.85
$CO2r_g$	[ton/$\mathrm{MWh_t}$]	0.19	0.19	0.19	0.19	0.19
$TxCN_g$	[€/$\mathrm{MWh_t}$]	2.50	2.50	2.50	2.50	2.50
TxE_g	[€/MWh]	1.00	1.00	1.00	1.00	1.00
TxI_g	[p.u.]	0.05	0.05	0.05	0.05	0.05
PCN_g	[€/$\mathrm{MWh_t}$]	20	20	20	20	20
Own_g	[p.u.]	1.00	0.90	1.00	1.00	0.90

not modify the behavior of the model as they only generate additional variables that have no impact in the objective function. However, they were used to calculate the theoretical individual income of turning on those units according to their reference generation profile. The second execution, referred as *Enforce UC*, used the model of the first execution but including constraints (5.8), (5.14), (5.15), (5.16), (5.17), (5.19), and (5.20), to enforce the commitment of the units. Finally, the third execution labeled as *Social welfare* is the same model as in the previous subsection, the one presented in Section 5.3.2.2 Mathematical formulation.

The resulting market price for the three models is displayed in Figure 5.12, whereas Table 5.5 shows the energy generated during each execution. It is important to note that according to Table 5.4 G3's initial power above $\underline{P}_g$ was 100MW. Therefore, those 180MW generated during the day are the 180MW it generates during the first hour of the day in order to shut-down, and it remains off the rest of the day. Note that this situation highlights the need to carefully consider the initial conditions in the equations, as with the parameter $Hmin_g^{sd}$ in equation (5.8). If such initial conditions were not considered, the mentioned equation would be infeasible for this case.

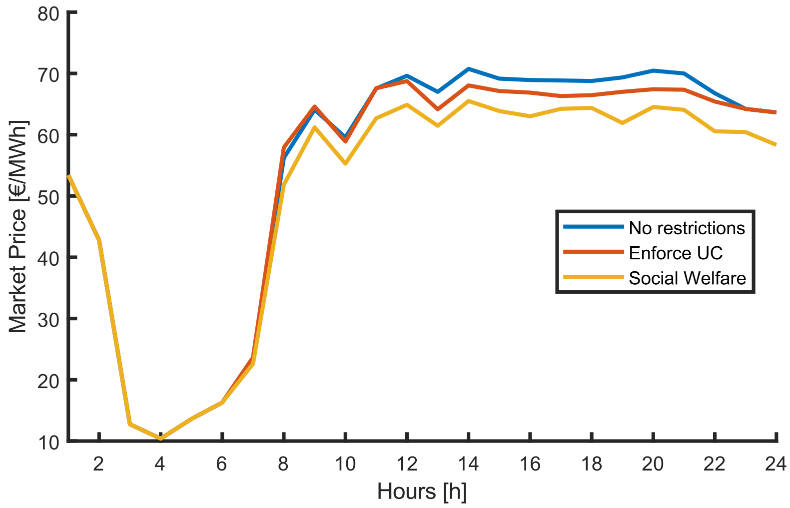


Figure 5.12: Market prices. Potential individual income case.

Table 5.5: Energy produced by each generation unit [MWh/day]. Potential individual income case.

Executions	G1	G2	G3	G4	G5	G6	Total
No restrictions	0	6118	180	0	5698	40800	52796
Enforce UC	0	5721	4166	0	5698	40800	56385
Social welfare	5914	6521	6217	5924	6511	40800	65963

5.4.2.1 No restrictions vs Enforce UC

In the first run, the optimizer prefers to leave uncommitted some units that individually could earn money (G1, G3, and G4) to increase the market price (presented in Figure 5.12) and thus earn more from the rest of the generation sold to the market (G2, G5 and G6). The potential individual profits (according to the reference generation profile) of each generation unit are displayed in Figure 5.13, where it can be seen that all units could be profitable (blue bar higher than yellow bar).

In the second run, by imposing the constraint that units that could have profits if committed using the reference generation profile must be committed, the optimizer connects G3. Units G1 and G4 are not connected because its generation with such profile becomes non-profitable as the market price decreases by increasing the generation of G3.

The unit that is turned on (G3) earns 43.73k€, whereas the units that remain connected earn less due to the decrease in market price. The final balance is that the operation is 20.48k€ less profitable but more compliant with market rules.

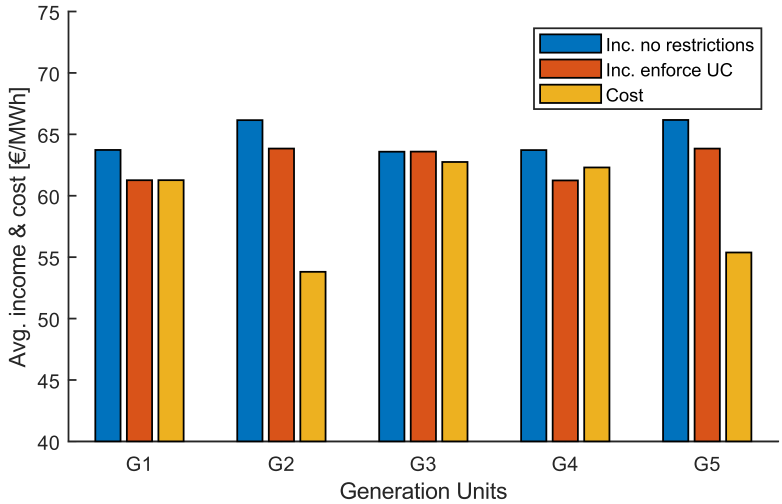


Figure 5.13: Potential average income of each generation unit with and without imposing individual constraints to force the commitment of the units that can have individual profits, and average cost of the proposed generation profile used for those constraints.

5.4.2.2 Enforce UC vs. Social welfare

When analyzing the results from the *Social welfare* execution, it is verified that the operation is 261.023k€ and 240.543k€ less profitable that with the *No restrictions* and *Enforce UC* options, respectively.

The situation is the opposite of the previous. Both models have an opposite optimization direction. The *Social welfare* execution runs into the constraint of not being able to generate more energy because the units cannot lose money individually. In contrast, the *Enforce UC* execution wants to withdraw energy from the market and encounter the obligation to produce. In this case, it is clear that the *Social Welfare equivalent optimization model* is always closer to the perfect competition scenario.

5.5 Conclusion

The first conclusion of this chapter is that pure profit maximization models are not helpful in market environments with regulations that limit the strategic behavior of the agents. They are not helpful because their results do not correspond to acceptable market outcomes, and therefore, they cannot be used directly to feed the tools used to build the offers and bids for the market. To solve this problem, two modeling approaches have been proposed.

The first approach consists of maintaining profit maximization as the model objective and adding additional constraints representing the market regulation where the company operates. In this way, strategic behaviors can be limited, but to what degree? The answer is that it depends. A formulation considering the real feasible operation has been proposed together with several simplifications, but they all rely on parameterization. The GenCo decides on this parameterization, and when doing so, it must be consistent with the rules of the market in which it operates and the freedom of the agents participating in it. At the end of the day (actually at 12 a.m. for the Iberian market), the actual signal from the GenCo to the market is not its own planning, but the bids it sends. Therefore, if these bids are prepared considering imprecise information, such as that obtained with a UC planning model that does not consider the reality of the market in which it is used, it is most likely that the GenCo's operation will be less efficient than if a more realistic model was used. Therefore, the second conclusion we can draw is that profit maximization models can be used if they are adapted to include regulatory constraints in accordance with the market rules.

The second approach consists of changing the model's objective from profit optimization to maximizing the estimated social welfare. In other words, try to replicate how a centralized operator would carry out the operation planning. This approach attempts to optimize the entire system's performance, but unlike a centralized entity, the individual agent has just partial information. The GenCo only has the detailed information of its own units and has to resort to a simplified representation of competitors and demand, for which it can construct residual demand curves using publicly available data, such as the bids sent to the market. The conclusion that can be extracted here is that an individual agent with at least some simplified information about the rest of the system is in a position to plan his own operation in a way that most closely resembles a perfect competition environment. Therefore, this model is highly recommended in market frameworks with very restrictive regulations.

Finally, as stated above, these two models are helpful for GenCos participating in the market. However, from the regulatory authorities' point of view, these models are also valuable tools to analyze expected behaviors of such GenCos participating in the market.

Chapter 6

Conclusions

This chapter lists the thesis's main conclusions and contrasts them with the objectives set out in the first chapter. Afterward, the most relevant original contributions will be summarized, as well as the papers produced during the research development. Finally, possible lines for future research works will be suggested.

6.1 Conclusions

This thesis has started analyzing the regulation affecting the electricity generation activity, with particular attention to the Gas Fired Units (GFUs), to detect possible particularities that affect the optimal operation planning. After this identification, a series of improvements to the Unit Commitment (UC) models have been proposed to take them into account in the optimization planning. Finally, an analysis of these particularities' importance and the need to take them into account in the UC models (using the proposed improvements) has been made. This analysis has been carried out through the presentation of case studies in which the results obtained using the standard and proposed models have been compared. In this way, not only the results of the proposed models are presented, but also numerical data are provided to support the benefits of using them versus not using them.

The following subsections present the results of the analysis of the regulation to which the generation units are subject and its implications (Section 6.1.1 Problem identification); a brief summary of the proposed modeling (Section 6.1.2 Proposed models); and the main conclusions drawn from the application of the proposed models (Section 6.1.3 Conclusions).

6.1.1 Problem identification

The different particularities that can affect the scheduling of the generation units are detailed below. For each of these particularities, the implications for the optimization models are listed.

The gas units draw the fuel they consume for electricity generation through a gas transmission network. In order to make use of this network, they have to reserve gas withdrawal capacity by paying a series of access tariffs (Third Party Access (TPA) tariffs). These tariffs are offered with different time horizons, with those of shorter duration being proportionally more expensive. Its implications are the following:

- It is necessary to consider the aggregate consumption of all the generation units of the same exit point of the network (usually the units located in the same power plant) since the TPA tariffs are paid for the total gas extracted from the access point. Therefore, the operation of each of the units cannot be separated from that of the others.

- The TPA contracting decisions cannot be separated from the units' scheduling. On the one hand, the final generation schedule, and therefore the consumption, depends on the costs and thus on the TPA capacity contracted. On the other hand, the amount of capacity to be contracted depends on the consumption from the planned generation.

- In the short term, it is necessary to decide whether to contract daily or monthly TPA tariffs. The consumption variables of each hour of the same day are linked when using daily tariffs and those of the whole month when contracting the monthly alternative.

- The cost of the TPA tariffs is not negligible as it represents over 10% of the total generation cost.

When there is a gas spot market where a Generation Company (GenCo) can acquire the needed gas for the operation of its GFUs, the following aspect should be considered:

- Regardless of how the GenCo purchases the gas, the spot market price is its cost benchmark because it represents the opportunity cost of its use as it is possible to sell it to the market. This can be understood as arbitrage between markets: if gas is cheap, it pays to take it from the gas market, use it to produce electricity, and sell that electricity in the electricity market, whereas if electricity is cheap, it pays to "take power from the electricity market" (not actually purchasing electricity, but deciding not to produce it) and sell that unused gas in the gas market.

- There may be the option of using the storage infrastructure of the gas network (paying the applicable tariffs) to increase the possibilities that the company has to make that arbitrage and reduce the average cost of the acquired gas.

- Large gas purchases can impact the gas market price. Consequently, the gas consumption of all the GFUs must be taken into account in the portfolio level to know the actual effect on the gas price and, therefore, the real impact of the gas acquisition cost. As with the TPA tariffs, this decision cannot be separated from the optimization of the GFUs operation planning itself.

Generation units are subject to a very diverse tax system that, depending on their characteristics, may have certain implications:

- Taxes may differ by generation technology or geographic area, so even identical units may have different taxation schemes.

- The taxes apply to different variables of the problem. Taxes applied on variables such as electricity generation or emissions do not represent a problem from a mathematical point of view. However, those that charge variables such as profit can be challenging. When an agent is small enough to be considered a price-taker, one can calculate the revenue directly during optimization by multiplying the price parameter by the energy quantity variable. Therefore, the tax can be considered by simply adding a parameter multiplying that expression. However, when the agent is large enough to be considered a price-maker, the price becomes a variable instead of a parameter, and the formulation becomes nonlinear. A usual solution is not to model the price variable but to model the revenues using income curves representing the company's total revenue as a function of the total energy produced. With this approach, it is impossible to particularize the taxes on the profit of each generator, having to resort to approximations with the associated error it entails.

There are generation assets whose operation is managed by one agent but whose ownership is shared by several.

- In the case of a price-maker agent that uses income curves to model revenue, it is impossible to ensure that these curves are well constructed unless the merit order of the generation units is known beforehand.

Planning models whose objective is profit maximization at the portfolio level without additional considerations can lead to solutions with strategic behavior.

- The regulation of electricity markets includes, among its goals, avoiding the possible exercise of market power by dominant players who might behave strategically in order to maximize their own profit. Therefore, if the solution of a short-term planning model leads to such strategic behavior, the model would lose its utility for a GenCo in planning its operation as it would not be aligned with the actual performance of the market.

6.1.2 Proposed models

As the purpose of this research is to bridge the gap between the state-of-the-art models and current industry needs, a complete self Unit Commitment (self-UC) model covering all considerations is presented in this thesis. However, to make the explanations easier to follow, and avoid superfluous complications, the main chapters offer detailed modeling for the topics they are focused on, whereas simplified equations are used for others. For example, this is the case for the treatment of Combined Cycle Gas Turbines (CCGTs) with multiple turbine configurations. The main chapters do not give special treatment to this aspect, but in Appendix B Combined Cycle Gas Turbines, the equations for modeling this type of unit and the changes to include this functionality are indicated.

Some of the developments presented in this document have been made in collaboration with the industry and are already implemented in models that are used on a daily basis, as is the case of the modeling of TPA tariffs. Other developments, such as those related to strategic behaviors, are more theoretical exercises that continue research lines previously discussed at Institute for Research in Technology (IIT) (García-González, 2000) for the hypothetical case of a GenCo being a price-maker agent.

The characteristics of the models presented in each of the chapters are detailed below.

- Chapter 3 Modeling of Third Party Access Tariffs and Portfolio Gas Purchases of CCGTs in the Self-Unit Commitment Problem
  - Optimal TPA contracting with daily or monthly options.
  - Gas purchases at the portfolio level and modeling of the price impact of such purchases.
  - Possibility of using the available storage infrastructure by paying the corresponding tariffs.
- Chapter 4 Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology
  - Modeling the individual revenues of each generation unit by discretizing the residual demand curves instead of using income curves.
  - Detailed representations of any kind of tax, including charges on market revenues.
  - Proper representation of generation assets shared ownership.
- Chapter 5 Introduction of regulatory criteria in the self-UC model
  - *Regulatory-constrained profit maximization model*: same model as in the previous chapter with additional constraints to limit strategic behaviors.
  - *Social Welfare equivalent optimization model*: same model as in the previous chapter but with the objective function of social welfare maximization and equations to calculate it.

6.1.3 Conclusions

Due to confidentiality issues, we could not use values of real generation units. Therefore, the data used for the case studies are fictitious but with realistic values, so the results on which these conclusions are based are within realistic range values that could be expected in actual cases. The main conclusions extracted from those study cases the are following.

In Chapter 3 Modeling of Third Party Access Tariffs and Portfolio Gas Purchases of CCGTs in the Self-Unit Commitment Problem it is found that the operation of GFUs is suboptimal if TPA contracting (which accounts for 10% of the generation costs) is disregarded, obtaining up to 4.2% worse results. Additionally, it is necessary to consider the impact on the gas price, and for the case in which it is allowed to use the gas storage infrastructure, the profits of the case study increased by 2.2%. Finally, the proposed model finds the optimal TPA contracting that is another finding of this research.

Chapter 4 Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology shows that, under certain circumstances, if taxes are not modeled correctly (specifically the market profit tax), situations arise where the generation units with the highest profit margin remain turned off whereas more expensive units are used. In addition, the error in the representation of generation plants with shared ownership is demonstrated during the construction of the income curves, an issue that the proposed model handles correctly.

Chapter 5 Introduction of regulatory criteria in the self-UC model showed how particular situations would lead profit maximization models to the exercise of market power and the necessity of limiting such behaviors to produce realistic outputs. Depending on the freedom degree allowed by the regulation in force, it will be more appropriate to use a model that tries to maximize the social welfare or a model more oriented to the company's profits with pertinent limitations.

6.2 Contributions

The main contributions of this thesis have been: 1) the identification of which aspects of the current regulation of the electricity and gas sectors were not adequately addressed by the state-of-the-art models, 2) to quantify their relevance from the perspective of a GenCo, and 3) to elaborate mathematical formulations that can be embedded in the optimization tool used by the GenCo to operate in real markets, or by the regulator in order to analyze the theoretical results of the market under certain hypotheses. In particular, these general contributions can be split as listed below:

- An analysis of the current European legislation that establishes the TPA system that a GenCo must take into account when planning the operation of its GFUs has been carried out.
- In order to optimize the operation more realistically, a detailed TPA cost rep-

resentation for the self-UC problem modeling has been proposed. The proposed formulation uses stochastic programming to deal with the uncertainty that naturally arises when optimizing periods of a month duration. Additionally, this model provides the optimal daily and monthly TPA contracting decisions to be determined by the GenCos, that otherwise would need to be determined by an additional specific model.

- The methodology used to assess the impact of the proper TPA modeling is also an original contribution. This methodology consisted of comparing the proposed formulation with the one found in the literature, computing the most optimistic cost parameters for the latter approach to establish a lower bound for the proposed method's usefulness, and testing the solutions from the stochastic optimization against an actual realization to perform an out-of-sample analysis.

- An analysis has been carried out regarding the different taxes applicable to the power generation activity and their implication on the self-UC scheduling depending on their nature (variables subject to taxation). This analysis has identified a complex taxation structure with different levies regarding technologies, power output, and geographical areas, that may depend on various administrations. Specifically, charges based on market income may be challenging for profit maximization models where prices are not input data.

- A stochastic model using discretized income curves has been proposed to consider the expenses associated with taxes and the possibility that different agents may share the generation assets ownership. This proposed model has been tested against the modeling approach using income curves and has been proved to perform better both in terms of the real profits obtained (computed ex-post with the original non-discretized data) and the error incurred by the model as the difference of the objective function value and the ex-post profits.

- Two modeling approaches have been proposed for the optimal short-term operation planning to act with a behavior similar to perfect competition situations. The first approach includes additional regulatory constraints in a pure profit maximization model to bring its solutions closer to perfect competition, and allowing the user of the model to graduate such gap. The second approach performs social welfare maximization from an agent's perspective using the publicly available data of its competitors and demand through residual demand curves. These two models would be of value to GenCos as they produce results closer to what can be done in reality, and also to regulatory authorities to analyze expected behaviors of such GenCos participating in the market.

- The proposed mathematical formulations allow for solving realistic cases regarding both size and conditions.

- A step-by-step guide has been developed for deploying an optimization model in a cloud infrastructure like those used in actual industry environments.

6.3 Publications

As a result of this thesis work, the following papers have been produced:

- *Impact of Gas Third Party Access in the Unit Commitment Optimal Solution*

  Presented in 2019 Institute of Electrical and Electronics Engineers (IEEE) Milan PowerTech (Otaola-Arca et al., 2019).

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

  Published in IEEE Transactions on Power Systems on 25 November 2020 (Otaola-Arca et al., 2021), and later presented in 2021 IEEE Madrid PowerTech.

- *Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology*:

  Submitted to IEEE Transactions on Power Systems on 28 February 2022.

- *Introduction of regulatory criteria in the self-UC model*:

  Working paper (Otaola-Arca & García-González, 2022)

6.4 Future research

During the development of this thesis, some topics have been identified that could be the subject of future research. The most relevant ones are detailed below and divided into two blocks. The first block presents the future work directly derived from the developments of this thesis, and the second block tries to go one step further, suggesting a possible roadmap of research lines that could be explored.

A) Future research topics derived from the thesis work:

   This thesis focuses on the operation planning models. One of the aspects that has been analyzed is how to consider the current regulation of TPA of the gas network in the optimization models. From a research point of view closer to the regulatory perspective, it could be studied the possible implications that the current TPA structure has on the optimality of the operation planning and its potential inefficiencies or areas of improvement. For this purpose, the proposed model would help compare the current system with other regulatory alternatives.

   Another aspect related to TPA would be its consideration in very short-term models that take into account both day-ahead and intraday markets. Instead of considering the monthly and daily TPA contracting alternatives, the decision regarding monthly contracting should be regarded as decided by a longer-term model, and the focus would be to optimize the right combination of daily and intraday capacity.

Continuing with the detailed modeling of the gas-related aspects, combining the optimization of the energy scheduling with that of the secondary reserve would be interesting. Considering both markets together in the planning has implications on the load level of the generating units to be able to sell regulation capacity. In addition to selling such capacity, during real-time, the generation of that energy may be required. If the GFUs sell reserve capacity, they must be able to produce the energy, implying there is an additional need for available gas and TPA capacity. However, as not all sold capacity would be required in real-time, considerations regarding the percentage of the time that additional power is actually needed and the uncertainty associates should be carefully considered.

B) Future research general topics:

The current tax scheme is complex, as it has different charges applied to generation technologies, geographic areas, and concepts. The market is designed in such a way that the technologies with the cheapest generation cost are the ones that are used. For that reason, some taxes are designed to generate incentives according to specific policies by changing the generation cost structure. For example, charges applied to CO_2 emissions seek to encourage the use of less polluting technologies. When these taxes are designed, the objectives are (or should be) generally clear. However, translating these objectives into effective incentives is a complex task. Considering the diversity of the tax structure affecting the power generation activity and the fact that these taxes depend on different administrations, it might be worthwhile to analyze whether the market signals generated by these taxes are appropriate according to the objectives they pursue.

Chapter 5 Introduction of regulatory criteria in the self-UC model presented a model to be used by a GenCo trying to act as it would in a situation of perfect competition. To this end, it maximizes social welfare by using residual demand curves as information from the rest of the system. This model is precisely aimed at avoiding results that contain strategic behaviors. However, these residual demand curves are built with the public information about the offers sent by the rest of the agents, over whom the GenCo has no detailed knowledge and certainly no control. Therefore, the competitors' strategic behaviors could be implicit in these residual demand curves. A topic to be studied are the implications of such competitors' behaviors on the GenCo's own operation planning, and to what extent having an estimation of these strategic offers is a valuable knowledge that the GenCo would use to change its way of acting.

Appendix A

General Unit Commitment formulation

The main objective of this thesis is to improve the modeling of Combined Cycle Gas Turbines (CCGTs) in short-term self Unit Commitment (self-UC) problems. To this end, specific improvements are proposed for these generating units, as well as for the set of all generators. In this annex, a state-of-the-art stochastic Unit Commitment (UC) formulation is presented as a base for the modifications/improvements proposed that are explained in the main chapters of the thesis. For that reason, the equations presented here are the technical constraints of the groups, such as ramp limits or coherence between start-up decisions and commitment status. However, the formulation of the objective function and cost calculation are specified according to what is to be analyzed in each case. Therefore, this section is not a complete model but rather a reference for the rest of the thesis.

The papers presented during the development of this thesis have used this same formulation as a basis. However, the version presented in this document unifies possible differences between those publications regarding the nomenclature.

Furthermore, it is important to note that this base formulation is not a novel contribution of this thesis but is inspired by its deterministic version in (Morales-España et al., 2013) and adapted to consider different scenarios. Therefore the contributions are the modifications proposed thought the main chapters, and a minor correction to the formulation from (Morales-España et al., 2013) presented in Appendix A.1 Initial conditions for start-up types.

A.1 Initial conditions for start-up types

The formulation regarding the type of start-up (modeled with equations (A.1a) and (A.1b) according to the authors in (Morales-España et al., 2013)) might not work correctly when the discretization of start-up types considers only a reduced number of them. This becomes an issue as it is common to consider just a few start-up types to keep the right balance between the accuracy and complexity of the optimization models.

$$\delta_{g,t,su} \leq \sum_{\substack{t' \in T \\ TmnS_{g,su} \leq t' \\ t' < TmnS_{g,su+1}}} [z_{g,t-t'}] \qquad \forall g \in G, su \in SU - \{\mathrm{SU}\}, t \in T, TmnS_{g,su+1} \leq t \tag{A.1a}$$

$$\delta_{g,t,su} = 0 \qquad \forall g \in G, su \in SU - \{\mathrm{SU}\}, t \in T, H^{\delta}_{g,su} < t < TmnS_{g,su+1} \tag{A.1b}$$

$$H^{\delta}_{g,su} = \begin{cases} 0 & if\ TmnS_{g,su+1} - TDo_g \leq 0 \\ TmnS_{g,su+1} - TDo_g & if\ TmnS_{g,su+1} - TDo_g > 0 \end{cases}$$

The data expressed in Table A.1 and represented in Figure A.1 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 A.1: 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

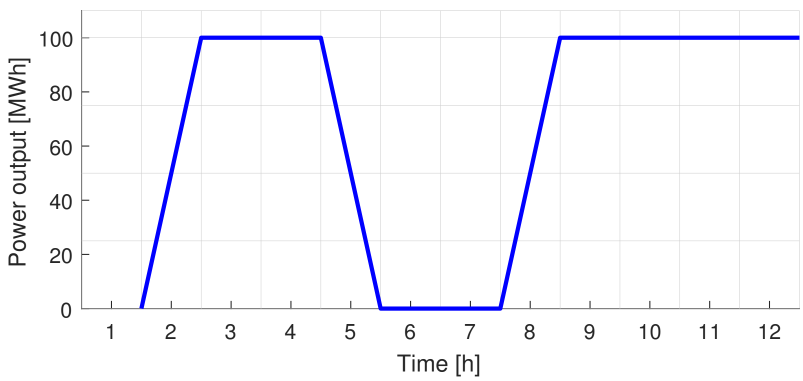


Figure A.1: Start-up during initial periods.

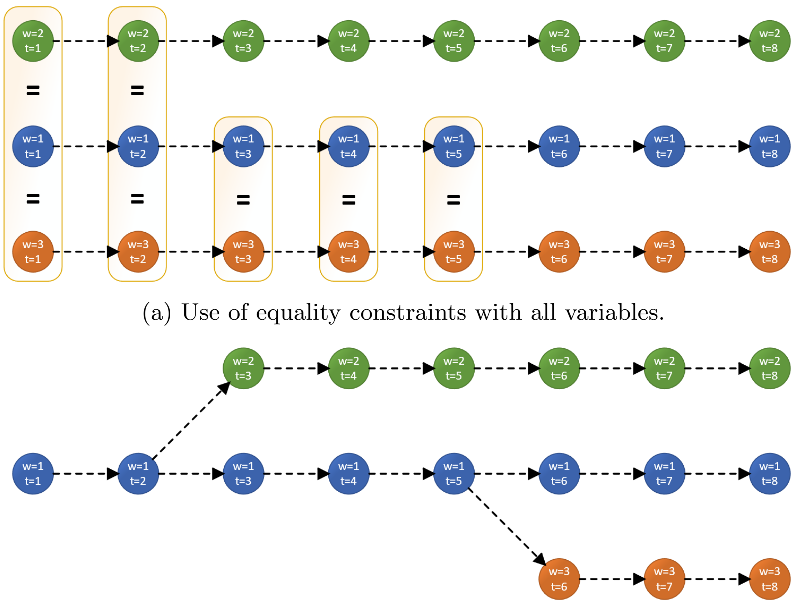
It can be concluded that the formulation fails when the time required in the warmest start-up maneuver is larger than the time required to perform the following actions: to start-up; to be connected the minimum up-time; to shut-down, to be disconnected the minimum downtime, and to start-up a second time.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

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 (A.1a) should be applied is defined in (A.2), (A.1b) is no longer used, and the calculation of $H^{\delta}_{g,su}$ is maintained.

$$\delta_{g,t,su} \leq \sum_{\substack{t' \in T \\ TmnS_{g,su} \leq t' \\ t' < TmnS_{g,su+1}}} [z_{g,t-t'}] \qquad \forall g \in G, su \in SU - \{\mathrm{SU}\}, t \in T, H^{\delta}_{g,su} \leq t \quad \text{(A.2)}$$

A.2 Uncertainty formulation

We have chosen the stochastic formulation to consider uncertainty. From the two options previously presented, using independent scenarios or using a tree structure, the latter has been selected. The main reason for choosing a stochastic formulation with a tree structure is its versatility. The deterministic version is a particular case with only one scenario, and the use of independent scenarios is another specific case where all scenario branchings occur in the first period.



(a) Use of equality constraints with all variables.

(b) Use of representative relations with minimum number of variables.

Figure A.2: Tree structure representation.

Regarding the mathematical formulation itself, Figure A.2 shows the two alternatives. On the one hand, the variables for all scenarios and time periods can be used, as in Figure A.2a. In this case, additional constraints such as (A.3) must be established to equal the variables that are common among different scenarios for specific periods. The definitions of the scenarios that are equal in each period are the following:

$\Omega^{w'}_{w,t}$ scenarios w' that are indistinguishable to scenario w at stage t.

$\Omega^{w'}_{w,d}$ scenarios w' that are indistinguishable to scenario w on day d.

$\Omega^{w'}_{w,dg}$ scenarios w' that are indistinguishable to scenario w on gas day dg.

$\Omega^{w'}_{w,mg}$ scenarios w' that are indistinguishable to scenario w in gas month mg.

$$x_{w,t} = x_{w',t} \qquad \forall w \in W, w' \in \Omega^{w'}_{w,t}, t \in T \tag{A.3a}$$

$$x_{w,d} = x_{w',d} \qquad \forall w \in W, w' \in \Omega^{w'}_{w,d}, d \in D \tag{A.3b}$$

$$x_{w,dg} = x_{w',dg} \qquad \forall w \in W, w' \in \Omega^{w'}_{w,dg}, dg \in DG \tag{A.3c}$$

$$x_{w,mg} = x_{w',mg} \qquad \forall w \in W, w' \in \Omega^{w'}_{w,mg}, mg \in MG \tag{A.3d}$$

For the example in Figure A.2a the definition of the set $\Omega^{w'}_{w,t}$ is $w' \in \Omega^{w'}_{w,t}$ for the following cases:

- $t = 1, w = 1, w' \in \{1, 2, 3\}$
- $t = 1, w = 2, w' \in \{1, 2, 3\}$
- $t = 1, w = 3, w' \in \{1, 2, 3\}$
- $t = 2, w = 1, w' \in \{1, 2, 3\}$
- $t = 2, w = 2, w' \in \{1, 2, 3\}$
- $t = 2, w = 3, w' \in \{1, 2, 3\}$
- $t = 3, w = 1, w' \in \{1, 3\}$
- $t = 3, w = 2, w' \in \{2\}$
- $t = 3, w = 3, w' \in \{1, 3\}$
- $t = 4, w = 1, w' \in \{1, 3\}$
- $t = 4, w = 2, w' \in \{2\}$
- $t = 4, w = 3, w' \in \{1, 3\}$
- $t = 5, w = 1, w' \in \{1, 3\}$
- $t = 5, w = 2, w' \in \{2\}$
- $t = 5, w = 3, w' \in \{1, 3\}$
- $t = 6, w = 1, w' \in \{1\}$
- $t = 6, w = 2, w' \in \{2\}$
- $t = 6, w = 3, w' \in \{3\}$
- $t = 7, w = 1, w' \in \{1\}$
- $t = 7, w = 2, w' \in \{2\}$
- $t = 7, w = 3, w' \in \{3\}$
- $t = 8, w = 1, w' \in \{1\}$
- $t = 8, w = 2, w' \in \{2\}$
- $t = 8, w = 3, w' \in \{3\}$

On the other hand, the option that has been chosen for this thesis, it is possible to define only those variables that can be different, as in Figure A.2b. If in a period there are two scenarios w and w' that are equal, only the variable of scenario w is used. When the variable of scenario w' has to be used, it is substituted by the variable of scenario

w. In this case, it is necessary to consider which scenario w is the representative of w' (the one that represented it before the branching). Sets $\Omega^{w'}_{w,period}$ must be redefined to be the representatives instead of being the set of common scenarios, and additional sets regarding the scenarios that exist in each period (Ω^{w}_{period}) are defined:

$\Omega^{w'}_{w,t}$	scenario w' that represents scenario w at period t. It is possible that $w' = w$.
$\Omega^{w'}_{w,d}$	scenario w' that represents scenario w at period d. It is possible that $w' = w$.
$\Omega^{w'}_{w,dg}$	scenario w' that represents scenario w at period dg. It is possible that $w' = w$.
$\Omega^{w'}_{w,mg}$	scenario w' that represents scenario w at period mg. It is possible that $w' = w$.
Ω^{w}_{t}	representative scenarios w at period t.
Ω^{w}_{d}	representative scenarios w at period d.
Ω^{w}_{dg}	representative scenarios w at period dg.
Ω^{w}_{mg}	representative scenarios w at period mg.

The equations are no longer defined for all scenarios w but instead they are defined for the scenarios that exist in each period: $\forall w \in W \rightarrow \forall w \in \Omega^{w}_{period}$. In addition, equations that involve several time periods or have summations over time must look for the representatives in those periods, for example, equations (A.4) and (A.6) have to be rewritten as (A.5) and (A.7).

$$A \cdot x_{w,t} + B \cdot y_{w,t-1} + C \leq 0 \qquad \forall w \in W \tag{A.4}$$

$$A \cdot x_{w,t} + B \cdot y_{w',t-1} + C \leq 0 \qquad \forall w \in \Omega^{w}_{t}, w' \in \Omega^{w'}_{w,t-1} \tag{A.5}$$

$$A \cdot x_{w,t} + \sum_{\substack{t' \in T \\ t-10<t' \leq t}} [B \cdot y_{w,t'}] + C \leq 0 \qquad \forall w \in W \tag{A.6}$$

$$A \cdot x_{w,t} + \sum_{\substack{t' \in T \\ t-10<t' \leq t \\ w' \in \Omega^{w'}_{w,t'}}} [B \cdot y_{w',t'}] + C \leq 0 \qquad \forall w \in \Omega^{w}_{t} \tag{A.7}$$

For the example in Figure A.2b the definition of the set $\Omega^{w'}_{w,t}$ is $w' \in \Omega^{w'}_{w,t}$ for the following cases:

- $t = 1, w = 1, w' = 1$
- $t = 1, w = 2, w' = 1$
- $t = 1, w = 3, w' = 1$
- $t = 2, w = 1, w' = 1$
- $t = 2, w = 2, w' = 1$
- $t = 2, w = 3, w' = 1$
- $t = 3, w = 1, w' = 1$
- $t = 3, w = 2, w' = 2$
- $t = 3, w = 3, w' = 1$
- $t = 4, w = 1, w' = 1$
- $t = 4, w = 2, w' = 2$
- $t = 4, w = 3, w' = 1$
- $t = 5, w = 1, w' = 1$
- $t = 5, w = 2, w' = 2$
- $t = 5, w = 3, w' = 1$
- $t = 6, w = 1, w' = 1$
- $t = 6, w = 2, w' = 2$
- $t = 6, w = 3, w' = 3$
- $t = 7, w = 1, w' = 1$
- $t = 7, w = 2, w' = 2$
- $t = 7, w = 3, w' = 3$
- $t = 8, w = 1, w' = 1$
- $t = 8, w = 2, w' = 2$
- $t = 8, w = 3, w' = 3$

And the definition of the set Ω_t^w is $w \in \Omega_t^w$ for the following cases:

- $t = 1, w \in \{1\}$
- $t = 2, w \in \{1\}$
- $t = 3, w \in \{1, 2\}$
- $t = 4, w \in \{1, 2\}$
- $t = 5, w \in \{1, 2\}$
- $t = 6, w \in \{1, 2, 3\}$
- $t = 7, w \in \{1, 2, 3\}$
- $t = 8, w \in \{1, 2, 3\}$

Another consideration regarding implementation convenience is to set the variables that are not used equal to zero (A.8). Although it is unnecessary since they do not participate in any equation, it is useful when analyzing results because solvers could give them random values without modifying the objective function.

$$x_{w,t} = 0 \qquad \forall w \notin \Omega_t^w, t \in T \tag{A.8a}$$

$$x_{w,d} = 0 \qquad \forall w \notin \Omega_d^w, d \in D \tag{A.8b}$$

$$x_{w,dg} = 0 \qquad \forall w \notin \Omega_{dg}^w, dg \in DG \tag{A.8c}$$

$$x_{w,mg} = 0 \qquad \forall w \notin \Omega_{mg}^w, mg \in MG \tag{A.8d}$$

Finally, there may be cases in which certain variables do not fit the tree structure of the input data. For example, in Chapter 4 Price-maker self-unit commitment considering shared ownership of generation units and differentiated taxes by technology a self-UC considering different price scenarios is presented. On the one hand, the power $pt_{w,g,t}$ may have different values for all scenarios. On the other hand, the commitment variable $v_{w,g,t}$ could have different values for each scenario according to its sets. However, the commitment is required to be unique in each hour and therefore does not follow the generic formulation. These special considerations, which will be explained in each case, would be solved by defining particular sets $x\Omega^{w'}_{w,period}$ (x = variable name; $period$ = t, d, dg, or mg) for the affected variables. Those $x\Omega^{w'}_{w,period}$ must replace the generic $\Omega^{w'}_{w,period}$ in the equations where they apply.

A.3 Unit Commitment technical constraints

This subsection details the formulation of the technical constraints of the generations units. The equations linking several time periods are all formulated to look to the past ($t-1$) instead of looking to the future ($t+1$). This method makes it more straightforward to implement the problem's solution with several sequential partial executions.

To ease the understanding of the equations, the order in which the terms appear in them is maintained. That is why there are equations in the form $-a + b < c$ instead of $b - a < c$, because there are other equations of the type $a - b < d$, and maintaining the order a, b facilitates its reading. All the time periods are considered hourly periods, and therefore, the energy generated during one hour is equal to the unit's power output. For clarity purposes, the multiplications by time periods have been omitted in the equations

Total power output of the units: power above $\underline{P}_g$ plus $\underline{P}_g$ when it is committed ($v_{w,g,t} = 1$). And the power of the start-up $PSU_{g,tu}$ and shut-down $PSD_{g,tu}$ trajectories when performing such maneuvers.

$$pt_{w,g,t} = \underline{P}_g \cdot v_{w,g,t} + p_{w,g,t} + \sum_{\substack{tu \in \Omega^{tu}_g \\ t' \in T \\ t' = t + TSU_g + 1 - tu \\ w' \in \Omega^{w'}_{w,t'}}} [PSU_{g,tu} \cdot y_{w',g,t'}] + \sum_{\substack{td \in \Omega^{td}_g \\ t' \in T \\ t' = t + 1 - td \\ w' \in \Omega^{w'}_{w,t'}}} [PSD_{g,td} \cdot z_{w',g,t'}]$$

$$\forall w \in \Omega^w_t, g \in G, t \in T \quad \text{(A.9)}$$

Units are forced to stop at minimum power output.

$$IP_g \leq \left(\overline{P}_g - \underline{P}_g\right)\left(IS_g - z_{w,g,t}\right) \qquad \forall w \in \Omega^w_t, g \in G, t \in \{1\} \quad \text{(A.10a)}$$

$$p_{w',g,t-1} \leq \left(\overline{P}_g - \underline{P}_g\right)\left(v_{w',g,t-1} - z_{w,g,t}\right) \qquad \forall w \in \Omega^w_t, w' \in \Omega^{w'}_{w,t-1}, g \in G, t \in T - \{1\} \quad \text{(A.10b)}$$

Units are forced to start at minimum power output.

$$p_{w,g,t} \leq \left(\overline{P}_g - \underline{P}_g\right)(v_{w,g,t} - y_{w,g,t}) \qquad \forall w \in \Omega_t^w, g \in G, t \in T \quad \text{(A.11)}$$

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

$$v_{w,g,t} + z_{w,g,t} - y_{w,g,t} = IS_g \qquad \forall w \in \Omega_t^w, g \in G, t \in \{1\} \quad \text{(A.12a)}$$

$$v_{w,g,t} + z_{w,g,t} - y_{w,g,t} = v_{w',g,t-1} \qquad \forall w \in \Omega_t^w, w' \in \Omega_{w,t-1}^{w'}, g \in G, t \in T - \{1\} \quad \text{(A.12b)}$$

Minimum time the units must be on after start-up.

$$\sum_{\substack{t' \in T \\ t-TmnOn_g < t' \\ t' \leq t \\ w' \in \Omega_{w,t'}^{w'}}} [y_{w',g,t'}] \leq v_{w,g,t} - IS_g \qquad \forall w \in \Omega_t^w, g \in G, t \in T, t \leq TmnOn_g - TUo_g \quad \text{(A.13a)}$$

$$\sum_{\substack{t' \in T \\ t-TmnOn_g < t' \\ t' \leq t \\ w' \in \Omega_{w,t'}^{w'}}} [y_{w',g,t'}] \leq v_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T, t > TmnOn_g - TUo_g \quad \text{(A.13b)}$$

Minimum time the units must be off after shut-down.

$$\sum_{\substack{t' \in T \\ t-TmnOff_g < t' \\ t' \leq t \\ w' \in \Omega_{w,t'}^{w'}}} [z_{w',g,t'}] \leq -v_{w,g,t} + IS_g \qquad \forall w \in \Omega_t^w, g \in G, t \in T, t \leq TmnOff_g - TDo_g \quad \text{(A.14a)}$$

$$\sum_{\substack{t' \in T \\ t-TmnOff_g < t' \\ t' \leq t \\ w' \in \Omega_{w,t'}^{w'}}} [z_{w',g,t'}] \leq -v_{w,g,t} + 1 \qquad \forall w \in \Omega_t^w, g \in G, t \in T, t > TmnOff_g - TDo_g \quad \text{(A.14b)}$$

Maximum decrease in unit power output between consecutive hours.

$$IP_g - p_{w,g,t} \leq RD_g \left(v_{w,g,t} + z_{w,g,t}\right) \qquad \forall w \in \Omega_t^w, g \in G, t \in \{1\} \tag{A.15a}$$

$$p_{w',g,t-1} - p_{w,g,t} \leq RD_g \left(v_{w,g,t} + z_{w,g,t}\right) \qquad \forall w \in \Omega_t^w, w' \in \Omega_{w,t-1}^{w'}, g \in G, t \in T - \{1\} \tag{A.15b}$$

Maximum increase in unit power output between consecutive hours.

$$-IP_g + p_{w,g,t} \leq RU_g \cdot v_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in \{1\} \tag{A.16a}$$

$$-p_{w',g,t-1} + p_{w,g,t} \leq RU_g \cdot v_{w,g,t} \qquad \forall w \in \Omega_t^w, w' \in \Omega_{w,t-1}^{w'}, g \in G, t \in T - \{1\} \tag{A.16b}$$

Relation between type of start-up and number of hours that the unit has been off according to the correction explained in Appendix A.1 Initial conditions for start-up types.

$$\delta_{w,g,t,su} \leq \sum_{\substack{t' \in T \\ t - TmnS_{g,su+1} < t' \\ t' \leq t - TmnS_{g,su} \\ w' \in \Omega_{w,t'}^{w'}}} \left[z_{w',g,t'}\right] \qquad \forall w \in \Omega_t^w, g \in G, su \in SU - \{\text{SU}\}, t \in T, H_{g,su}^{\delta} \leq t \tag{A.17}$$

$$H_{g,su}^{\delta} = \begin{cases} 0 & if\ TmnS_{g,su+1} - TDo_g \leq 0 \\ TmnS_{g,su+1} - TDo_g & if\ TmnS_{g,su+1} - TDo_g > 0 \end{cases}$$

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

$$\sum_{su \in SU} \left[\delta_{w,g,t,su}\right] = y_{w,g,t} \qquad \forall w \in \Omega_t^w, g \in G, t \in T \tag{A.18}$$

Appendix B

Combined Cycle Gas Turbines

The minimum elements to produce electricity using gas are displayed in Figure B.1: a compressor, a combustion chamber, a Gas Turbine (GT), and an alternator (the compressor, the combustion chamber and the expansion in turbine itself are usually referred as the gas turbine). This setting is called a simple cycle.

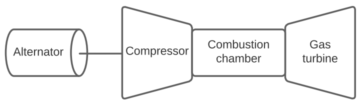


Figure B.1: Simple cycle: alternator + compressor + combustion chamber + Gas Turbine.

However, in this simple cycle a lot of heat is wasted. Therefore, in order to take advantage of all that wasted heat, a combined cycle is used. The combined cycle consists of generating additional electricity using a Steam Turbine (ST) whose steam is generated with the heat excess from the gas turbine, as shown in Figure B.2. The main elements of a combined cycle are the following:

1. Gas Turbine (compression+combustion+expansion): burns fuel to produce electricity.
    - The air is compressed and mixed with the fuel to produce a combustion and move a turbine.
    - The turbine drives an alternator to produce electricity.
2. Heat Recovery Steam Generator: produces steam using heat excess from the GT.
    - The Heat Recovery Steam Generator (HRSG) uses the heat excess from the gas turbine, that would otherwise be wasted, to produce steam.
    - It can produce steam at different pressure levels (low, intermediate and high).

- The HRSG can introduce additional fuel to be burned with the excess of O_2 from the GT to increase the amount of steam generated.

3. Steam Turbine: uses steam to produce electricity.

    - The ST uses the steam to drive an alternator to produce electricity.

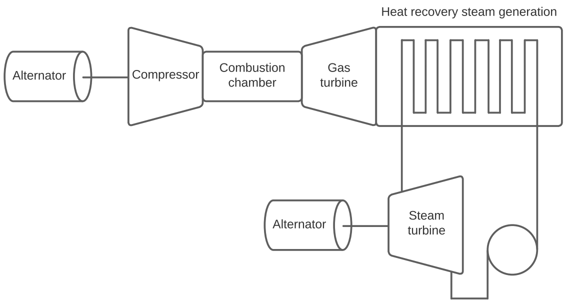


Figure B.2: Combined cycle: simple cycle + Heat Recovery Steam Generator + Steam Turbine.

Using a GT with a HRSG and a ST is the minimum to run a combined cycle. However, a single ST can use the steam produced by multiple GTs with HRSGs. For example, a power plant could have 4 GTs with 4 HRSGs and 1 ST as the one shown in Figure B.3. What is important, is that during the operation, the power plant could be running using several different configurations. For example, it could use 1 GT + 1 HRSG +1 ST or 4 GTs + 4 HRSGs +1 ST.

As a real example, Table B.1 shows the characteristics of three different options in which a commercial gas turbine is available. As a simple cycle, as a combined cycle with one GT and one ST (1x1), or as a combined cycle with two GTs and one ST (2x1). It can be seen that switching from simple to a combined cycle comports a substantial increase in efficiency (44.0% $\rightarrow$ 64.1%), whereas the change from 1x1 to 2x1 has a very slight improvement in efficiency (64.1% $\rightarrow$ 64.3%), but serves to increase the power output considerably (838MW $\rightarrow$ 1680MW).

Table B.1: Options for the 9HA.02 gas turbine (General Electric)[1].

	Simple cycle	1x1	2x1
Net output [MW]	571	838	1680
Net heat rate [Btu/kWh, LHV]	7740	5320	5306
Net heat rate [kJ/kWh, LHV]	8166	5613	5598
Net efficiency [%, LHV]	44.0	64.1	64.3
Ramp Rate [MW/minute]	88	88	176
Startup Time [RR Hot, Minutes]	23	<30	<30

[1] https://www.ge.com/gas-power/products/gas-turbines/9ha

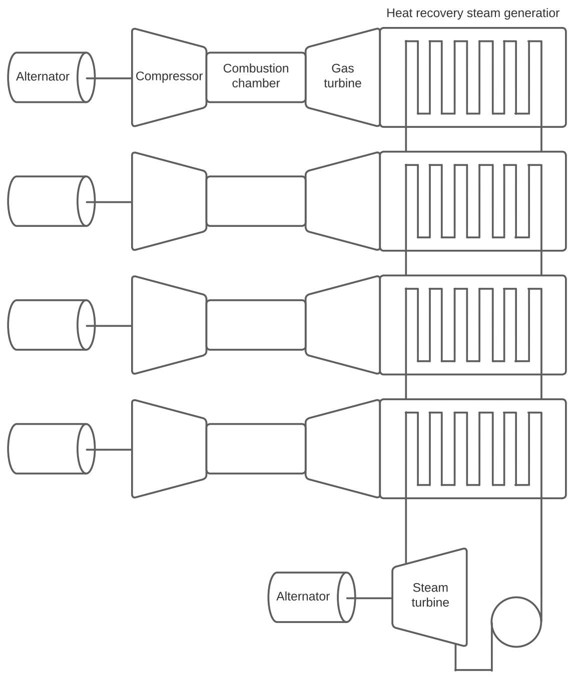


Figure B.3: Combined cycle with multiple GTs. The ST can be used with 1-4 GTs.

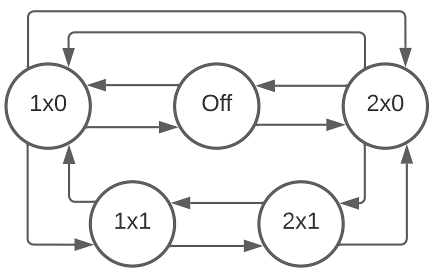


Figure B.4: Possible transitions between configurations of a generation unit with 2 GTs and 1 ST.

B.1 Formulation

There are three main option for modeling the multiple operating configurations of the Combined Cycle Gas Turbine (CCGT):

- Aggregate modeling: This representation ignores all the different operation configurations and represents CCGT as a single thermal unit representing the characteristics of the whole.
- Component modeling: The CCGT is not represented as a whole, but by modeling

each part of the system (boilers, compressors, GT, HRSG, ST, etc.). The excess of complexity arising from its high level of detail makes this representation not the most suitable for Unit Commitment (UC) scheduling

- Configuration-based modeling: The different operating modes are represented and treated as mutually exclusive.

Amongst the formulations for implementing the turbine configuration in the UC scheduling modeling tried during the development of the thesis, the one proposed in (Morales-España et al., 2016) was the best regarding performance. In (Morales-España et al., 2016) the authors present a tight and compact formulation following the configuration-based approach and is generic, supporting any configuration of gas and steam turbines.

This section presents an upgraded version of the formulation that includes the start-up and shut-down trajectories. Appendix B.2 Implementation specifies the changes that would have to be performed to adapt the formulation presented through the thesis in case generation units with multiple configurations were present. The nomenclature presented was adapted to be consistent with the rest of the thesis.

B.1.1 Nomenclature

Domain definitions:

- Reals: $\mathbb{R}$
- Non-negative reals: $\mathbb{R}^+ = \{x : x \geq 0, x \in \mathbb{R}\}$
- Per unit: $\mathbb{P} = \{x : 0 \leq x \leq 1, x \in \mathbb{R}\}$
- Binary: $\mathbb{B} = \{0, 1\}$
- Integers: $\mathbb{Z}$
- Non-neg. integers: $\mathbb{Z}^+ = \{x : x \geq 0, x \in \mathbb{Z}\}$

Sets

$tc, tc' \in TC$	Turbine configurations (operation modes) {off, 1x1, 2x1,...}.
Ω_g^{tc}	Turbine configurations feasible for generator g.
$\Omega_{g,tc}^{tc'}$	Feasible transitions between turbine configurations ($tc \neq tc'$) for generator g.
$\Omega_{g,tc}^{tu}$	Hourly time periods of the start-up trajectories of each tc {1 to TU}.
$\Omega_{g,tc}^{td}$	Hourly time periods of the shut-down trajectories of each tc {1 to TU}.

Variables

$v_{w,g,t,tc}^{tc} \in \mathbb{B}$	Commitment status of configuration tc, of generator g at hour t.

$v^{\rightarrow tc}_{w,g,t,tc,tc'} \in \mathbb{B}$ Transition between turbine configurations $tc \rightarrow tc'$.

$p^{tc}_{w,g,t,tc} \in \mathbb{R}^{+}$ Power generated over $\underline{P}^{tc}_{g,tc}$ by generator g at hour t [MWh].

Parameters

$IS^{tc}_{g,tc} \in \mathbb{B}$ Initial commitment status of mode tc of generator g.

$IP^{tc}_{g,tc} \in \mathbb{R}^{+}$ Initial power output over $\underline{P}^{tc}_{g,tc}$ of generator g [MWh].

$TmnOn^{tc}_{g,tc} \in \mathbb{Z}^{+}$ Minimum tc uptime of generator g [h].

$TmnOff^{tc}_{g,tc} \in \mathbb{Z}^{+}$ Minimum tc downtime of generator g [h].

$TUo^{tc}_{g,tc} \in \mathbb{Z}^{+}$ Time that generator g mode tc has been on before the optimization period [h].

$TDo^{tc}_{g,tc} \in \mathbb{Z}^{+}$ Time that generator g mode tc has been down before the optimization period [h].

$\overline{P}^{tc}_{g,tc} \in \mathbb{R}^{+}$ Maximum power output of generator g using configuration tc [MW].

$\underline{P}^{tc}_{g,tc} \in \mathbb{R}^{+}$ Minimum power output of generator g using configuration tc [MW].

$RU^{tc}_{g,tc} \in \mathbb{R}^{+}$ Ramp-up rate of generator g in mode tc [MW/h].

$RU^{\rightarrow tc}_{g,tc,tc'} \in \mathbb{R}^{+}$ Ramp-up rate of generator g switching between modes $tc \rightarrow tc'$ [MW/h].

$RD^{tc}_{g,tc} \in \mathbb{R}^{+}$ Ramp-down rate of generator g in mode tc [MW/h].

$RD^{\rightarrow tc}_{g,tc,tc'} \in \mathbb{R}^{+}$ Ramp-down rate of generator g switching between modes $tc \rightarrow tc'$ [MW/h].

$CNmn^{tc}_{g,tc} \in \mathbb{R}^{+}$ Consumption at $\underline{P}^{tc}_{g,tc}$ of generator g [$\mathrm{MWh_t}$/h].

$CNvr^{tc}_{g,tc} \in \mathbb{R}^{+}$ Variable consumption of generator g in mode tc [$\mathrm{MWh_t}$/MWh].

$CNtrv^{\rightarrow tc}_{g,tc,tc'} \in \mathbb{R}^{+}$ Consumption of the transition between modes $tc \rightarrow tc'$ of generator g [$\mathrm{MWh_t}$/h].

$PSU^{tc}_{g,tu,tc} \in \mathbb{R}^{+}$ Power output of generator g at step tu of the start-up trajectory of mode tc [MW].

$PSD^{tc}_{g,td,tc} \in \mathbb{R}^{+}$ Power output of generator g at step td of the shut-down trajectory of mode tc [MW].

$TSU^{tc}_{g,tc} \in \mathbb{Z}^{+}$ Mode tc start-up time of generator g [h].

$TSD^{tc}_{g,tc} \in \mathbb{Z}^{+}$ Mode tc shut-down time of generator g [h].

B.1.2 Equations

Total power output of the units: power above $\underline{P}_{g,tc}^{tc}$ plus $\underline{P}_{g,tc}^{tc}$ when it is committed ($v_{w,g,t,tc}^{tc} = 1$). And the power of the start-up $PSU_{g,tu,tc}^{tc}$ and shut-down $PSD_{g,tu,tc}^{tc}$ trajectories when performing such maneuvers.

$$\begin{aligned}
pt_{w,g,t} = & \sum_{tc \in \Omega_g^{tc \neq off}} \left[\underline{P}_{g,tc}^{tc} \cdot v_{w,g,t,tc}^{tc} + p_{w,g,t,tc}^{tc} \right] \\
& + \sum_{\substack{tc = off \\ tc' \in \Omega_{g,tc}^{tc' \neq off}}} \sum_{tu \in \Omega_{g,tc' \neq off}^{tu}} \left[PSU_{g,tu,tc'}^{tc} \cdot \sum_{\substack{w' \in \Omega_{w,t'}^{w'} \\ t' \in T \\ t' = t + TSU_{g,tc'}^{tc} + 1 - tu}} \left[v_{w',g,t',tc,tc'}^{\rightarrow tc} \right] \right] \\
& + \sum_{\substack{tc = off \\ tc' \in \Omega_{g,tc}^{tc' \neq off}}} \sum_{td \in \Omega_{g,tc \neq off}^{td}} \left[PSD_{g,td,tc'}^{tc} \cdot \sum_{\substack{w' \in \Omega_{w,t'}^{w'} \\ t' \in T \\ t' = t + 1 - td}} \left[v_{w',g,t',tc',tc}^{\rightarrow tc} \right] \right] \\
& \hfill \forall w \in \Omega_t^w, g \in G, t \in T \quad \text{(B.1)}
\end{aligned}$$

Operation modes are mutually exclusive, and the unit has to be always in one of the modes.

$$\sum_{tc \in \Omega_g^{tc}} \left[v_{w,g,t,tc}^{tc} \right] = 1 \qquad \forall w \in \Omega_t^w, g \in G, t \in T \quad \text{(B.2a)}$$

Coherence between the commitment status of the modes and the transition decisions between them.

$$v_{w,g,t,tc}^{tc} - IS_{g,tc}^{tc} = \sum_{tc' \in \Omega_{g,tc}^{tc'}} \left[v_{w,g,t,tc',tc}^{\rightarrow tc} - v_{w,g,t,tc,tc'}^{\rightarrow tc} \right]$$
$$\forall w \in \Omega_t^w, g \in G, t \in \{1\}, tc \in TC - \{off\} \quad \text{(B.3a)}$$

$$v_{w,g,t,tc}^{tc} - v_{w',g,t-1,tc}^{tc} = \sum_{tc' \in \Omega_{g,tc}^{tc'}} \left[v_{w,g,t,tc',tc}^{\rightarrow tc} - v_{w,g,t,tc,tc'}^{\rightarrow tc} \right]$$
$$\forall w \in \Omega_t^w, w' \in \Omega_{w,t-1}^{w'}, g \in G, t \in T - \{1\}, tc \in TC - \{off\} \quad \text{(B.3b)}$$

Limit the power output above $\underline{P}_{g,tc}^{tc}$ of each configuration and make it zero when the the unit is not in that mode.

$$p_{g,t,tc}^{tc} \leq (\overline{P}_{g,tc}^{tc} - \underline{P}_{g,tc}^{tc}) \cdot v_{w,g,t,tc}^{tc} \qquad \forall w \in \Omega_t^w, g \in G, t \in T, tc \in TC - \{off\} \quad \text{(B.4)}$$

Minimum time that each turbine configuration must be on.

$$\sum_{\substack{t-TmnOn^{tc}_{g,tc}+1\leq tt\\ tt\leq t\\ tc'\in\Omega^{tc'}_{g,tc}}} \left[v^{\rightarrow tc}_{w,g,tt,tc',tc}\right] + IS^{tc}_{g,tc} \leq v^{tc}_{w,g,t,tc}$$

$$\forall w\in\Omega^{w}_{t}, g\in G, t\in T, t\leq TmnOn^{tc}_{g,tc} - TUo^{tc}_{g,tc}, tc\in TC \qquad \text{(B.5a)}$$

$$\sum_{\substack{t-TmnOn^{tc}_{g,tc}+1\leq tt\\ tt\leq t\\ tc'\in\Omega^{tc'}_{g,tc}}} \left[v^{\rightarrow tc}_{w,g,tt,tc',tc}\right] \leq v^{tc}_{w,g,t,tc}$$

$$\forall w\in\Omega^{w}_{t}, g\in G, t\in T, t> TmnOn^{tc}_{g,tc} - TUo^{tc}_{g,tc}, tc\in TC \qquad \text{(B.5b)}$$

Minimum time that each turbine configuration must be off.

$$\sum_{\substack{t-TmnOff^{tc}_{g,tc}+1\leq tt\\ tt\leq t\\ tc'\in\Omega^{tc}_{g,tc'}}} \left[v^{\rightarrow tc}_{w,g,tt,tc,tc'}\right] + 1 - IS^{tc}_{g,tc} \leq 1 - v^{tc}_{w,g,t,tc}$$

$$\forall w\in\Omega^{w}_{t}, g\in G, t\in T, t\leq TmnOff^{tc}_{g,tc} - TDo^{tc}_{g,tc}, tc\in TC \qquad \text{(B.6a)}$$

$$\sum_{\substack{t-TmnOff^{tc}_{g,tc}+1\leq tt\\ tt\leq t\\ tc'\in\Omega^{tc}_{g,tc'}}} \left[v^{\rightarrow tc}_{w,g,tt,tc,tc'}\right] \leq 1 - v^{tc}_{w,g,t,tc}$$

$$\forall w\in\Omega^{w}_{t}, g\in G, t\in T, t> TmnOff^{tc}_{g,tc} - TDo^{tc}_{g,tc}, tc\in TC \qquad \text{(B.6b)}$$

Maximum decrease in unit power output between consecutive hours.

$$-p^{tc}_{w,g,t,tc} + IP^{tc}_{g,tc} - \sum_{tc'\in\Omega^{tc'\neq off}_{g,tc}} \left[IP^{tc}_{g,tc'}\right] \leq IS^{tc}_{g,tc}\cdot RD^{tc}_{g,tc}$$

$$+\sum_{tc'\in\Omega^{tc'}_{g,tc}} \left[v^{\rightarrow tc}_{w,g,t,tc,tc'}(-RD^{tc}_{g,tc} - \underline{P}^{tc}_{g,tc} + RD^{\rightarrow tc}_{g,tc,tc'} + \underline{P}^{tc}_{g,tc'})\right]$$

$$\forall w\in\Omega^{w}_{t}, g\in G, t\in\{1\}, tc\in TC-\{off\} \qquad \text{(B.7a)}$$

$$-p^{tc}_{w,g,t,tc} + p^{tc}_{w',g,t-1,tc} - \sum_{tc'\in\Omega^{tc'\neq off}_{g,tc}} \left[p^{tc}_{w,g,t,tc'}\right] \leq v^{tc}_{w',g,t-1,tc}\cdot RD^{tc}_{g,tc}$$

$$+\sum_{tc'\in\Omega^{tc'}_{g,tc}} \left[v^{\rightarrow tc}_{w,g,t,tc,tc'}(-RD^{tc}_{g,tc} - \underline{P}^{tc}_{g,tc} + RD^{\rightarrow tc}_{g,tc,tc'} + \underline{P}^{tc}_{g,tc'})\right]$$

$$\forall w\in\Omega^{w}_{t}, w'\in\Omega^{w'}_{w,t-1}, g\in G, t\in T-\{1\}, tc\in TC-\{off\} \qquad \text{(B.7b)}$$

Maximum increase in unit power output between consecutive hours.

$$p^{tc}_{w,g,t,tc} - IP^{tc}_{g,tc} - \sum_{tc' \in \Omega^{tc' \neq off}_{g,tc}} \left[IP^{tc}_{g,tc'}\right] \leq v^{tc}_{w,g,t,tc} \cdot RU^{tc}_{g,tc}$$
$$+ \sum_{tc' \in \Omega^{tc'}_{g,tc}} \left[v^{\to tc}_{w,g,t,tc',tc}(-RU^{tc}_{g,tc} - \underline{P}^{tc}_{g,tc} + RU^{\to tc}_{g,tc',tc} + \underline{P}^{tc}_{g,tc'})\right]$$
$$\forall w \in \Omega^w_t, g \in G, t \in \{1\}, tc \in TC - \{off\} \quad \text{(B.8a)}$$

$$p^{tc}_{w,g,t,tc} - p^{tc}_{w',g,t-1,tc} - \sum_{tc' \in \Omega^{tc' \neq off}_{g,tc}} \left[p^{tc}_{w',g,t-1,tc'}\right] \leq vx_{w,g,t,tc} \cdot RU^{tc}_{g,tc}$$
$$+ \sum_{tc' \in \Omega^{tc'}_{g,tc}} \left[v^{\to tc}_{w,g,t,tc',tc}(-RU^{tc}_{g,tc} - \underline{P}^{tc}_{g,tc} + RU^{\to tc}_{g,tc',tc} + \underline{P}^{tc}_{g,tc'})\right]$$
$$\forall w \in \Omega^w_t, w' \in \Omega^{w'}_{w,t-1}, g \in G, t \in T - \{1\}, tc \in TC - \{off\} \quad \text{(B.8b)}$$

Consumption of each unit depending on the generation of in each mode.

$$cnG_{w,g,t} = \sum_{\substack{tc \in \Omega^{tc}_g \\ tc' \in \Omega^{tc'}_{g,tc \neq off}}} \left[CNtrv^{\to tc}_{g,tc,tc'} \cdot v^{\to tc}_{w,g,t,tc,tc'}\right]$$
$$+ \sum_{tc \in \Omega^{tc \neq off}_g} \left[CNmn^{tc}_{g,tc} \cdot v^{tc}_{w,g,t,tc} + CNvr^{tc}_{g,tc} \cdot p^{tc}_{w,g,t,tc}\right]$$
$$\forall w \in \Omega^w_t, g \in G, t \in T \quad \text{(B.9)}$$

Relation between the power output of the generator and the active residual demand curve segments uaing the maximum power out of all possible configurations

$$apt_{w,i,g,t} \leq a_{w,i,t} \cdot \max_{tc \in \Omega^{tc \neq off}_g} [\overline{P}^{tc}_{g,tc}] \qquad \forall w \in \Omega^w_t, g \in G, t \in T, i \in \Omega^i_{w,t} \quad \text{(B.10)}$$

B.2 Implementation

The following lists present the relation between the elements of the standard formulation that have to be substituted and the ones in the model-based alternative. Element denoted as $*$ are those that do not have any correspondence on the standard version. Similar concepts are grouped with brackets.

Variables:

- $p_{w,g,t} \to p^{tc}_{w,g,t,tc}$
- $v_{w,g,t} \to v^{tc}_{w,g,t,tc}$
- $\begin{cases} y_{w,g,t} & \to v^{\to tc}_{w,g,t,tc=off,tc' \neq off} \\ z_{w,g,t} & \to v^{\to tc}_{w,g,t,tc \neq off,tc'=off} \\ * & \to v^{\to tc}_{w,g,t,tc \neq off,tc' \neq off} \end{cases}$

Parameters:

- $IS_g \rightarrow IS_{g,tc}^{tc}$
- $IP_g \rightarrow IP_{g,tc}^{tc}$
- $TmnOn_g \rightarrow TmnOn_{g,tc}^{tc}$
- $TmnOff_g \rightarrow TmnOff_{g,tc}^{tc}$
- $TUo_g \rightarrow TUo_{g,tc}^{tc}$
- $TDo_g \rightarrow TDo_{g,tc}^{tc}$
- $\overline{P}_g \rightarrow \overline{P}_{g,tc}^{tc}$
- $\underline{P}_g \rightarrow \underline{P}_{g,tc}^{tc}$
- $RU_g \rightarrow \begin{cases} RU_{g,tc}^{tc} \\ RU_{g,tc,tc'}^{\rightarrow tc} \end{cases}$
- $RD_g \rightarrow \begin{cases} RD_{g,tc}^{tc} \\ RD_{g,tc,tc'}^{\rightarrow tc} \end{cases}$
- $\begin{cases} CNsu_{g,su} & \rightarrow CNtrv_{g,tc=0,tc'\neq 0}^{\rightarrow tc} \\ CNsd_g & \rightarrow CNtrv_{g,tc\neq 0,tc'=0}^{\rightarrow tc} \\ * & \rightarrow CNtrv_{g,tc\neq 0,tc'\neq 0}^{\rightarrow tc} \end{cases}$
- $CNmn_g \rightarrow CNmn_{g,tc}^{tc}$
- $CNvr_g \rightarrow CNvr_{g,tc}^{tc}$
- $PSU_{g,tu} \rightarrow PSU_{g,tu,tc}^{tc}$
- $PSD_{g,td} \rightarrow PSD_{g,td,tc}^{tc}$
- $TSU_g \rightarrow TSU_{g,tc}^{tc}$
- $TSD_g \rightarrow TSD_{g,tc}^{tc}$

Equations:

- (A.9) → (B.1)
- $\begin{Bmatrix} \text{(A.10)} \\ \text{(A.11)} \\ \text{(A.12)} \end{Bmatrix} \rightarrow \begin{cases} \text{(B.2)} \\ \text{(B.3)} \\ \text{(B.4)} \end{cases}$
- (A.13) → (B.5)
- (A.14) → (B.6)
- (A.15) → (B.7)
- (A.16) → (B.8)
- (3.9) → (B.9)
- (4.8) → (B.10)

Appendix C

Cloud implementation (AWS)

In the business world, running optimization models on personal computers is becoming less common, with cloud-based applications being the norm. These professional applications run the optimization models on servers such as those offered by Amazon Web Services (AWS)[1], Azure (Microsoft)[2], or Google Cloud[3].

The development of this thesis has been closely linked to real projects in the industry. Thanks to this collaboration, improvements such as the Combined Cycle Gas Turbines (CCGTs)' cost structure detailed representation have already been implemented in real applications. Taking advantage of all the knowledge gained from this collaboration, this annex presents a basic example of how to run an optimization model using AWS services.

The complexity of the industrial-level processes is much greater than the example presented here. This complexity arises from the fact that in a real environment, several different models may have to be synchronized, the data exchange among them and with other applications have to be consistent, and the models may be run by users that may have different privilege access (execute, change data, see results, etc.), among others. However, this example serves to bring the understanding of how things work in industry a little closer to a more research-focused environment.

The remaining of this chapter is organized as follow:

- Appendix C.1 General description explains how the the process works.
- Appendix C.2 Docker container creation explains how to create the docker container where the model will run.
- Appendix C.3 Amazon Web Services setup presents is a graphical guide to configure AWS to run the model.

[1] https://aws.amazon.com
[2] https://azure.microsoft.com
[3] https://cloud.google.com

C.1 General description

When developing an application, the platform for which it will be developed must be taken into account. This means that it may be necessary to have different versions depending on the Operating System (OS) on which it will run. An alternative is to use a container, which has everything required to run the application and makes its execution independent of the OS. The most widely used tool to create these containers is Docker. According to the official Docker website[4], the definition of a container is the following:

" A container is a standard unit of software that packages up code and all its dependencies so the application runs quickly and reliably from one computing environment to another. A Docker container image is a lightweight, standalone, executable package of software that includes everything needed to run an application: code, runtime, system tools, system libraries and settings."

" Container images become containers at runtime and in the case of Docker containers – images become containers when they run on Docker Engine. Available for both Linux and Windows-based applications, containerized software will always run the same, regardless of the infrastructure. Containers isolate software from its environment and ensure that it works uniformly despite differences for instance between development and staging."

For this example, a container image containing all the code needed to run the optimization model is created and stored in the AWS container images repository Elastic Container Registry (ECR) for later use.

The container uses Ubuntu (Linux) as the OS, and the model has been programmed in Python, using the Pyomo library (it allows to express the equations algebraically in a similar way as other programs such as General Algebraic Modeling Language (GAMS)). Cplex is used as a solver, but since we did not have an independent license, it is used through GAMS (when Pyomo calls the optimizer, instead of calling Cplex directly, it calls GAMS to use Cplex). An Optimizer could be called directly to make the execution independent from private applications such as GAMS. In that case, all the steps to install GAMS should substituted by the proper instructions to install a different optimizer.

The folder structure in the container is shown in Figure C.1. A Python virtual environment explicitly created for the model, with all the necessary packages (Pyomo, Pandas, etc.), is used for the execution. The file `model.py` is the main script, the one that will be called when the container is instanced in the cluster. This script uses the functions from the files `gilito.py` (containing everything related to the optimization), and `data_S3.py` (containing the functions to download/upload data from/to AWS storage service Simple Storage Service (S3)). These functions for downloading the data and uploading the results are shown in Listing 2. When data is downloaded, the `data` folder is created with the contents of the `par` and `set` folders. When data is uploaded, the entire `data` folder is uploaded, including both the results in the `output` folder and the original `par`,

[4] https://www.docker.com/resources/what-container

and `set` folders to keep both output and input together.

```
/opt/Gilito              Project main directory
├ .venv                  Python virtual environment
├ src
│ ├ gilito.py            Optimization model
│ └ data_S3.py           Functions to interact with S3
├ scripts
│ └ model.py             Main script: uses function from Gilito.py and data_S3.py
├ data
│ ├ input
│ │ ├ par
│ │ │ └ *.csv            Input parameters (one file per parameter)
│ │ └ set
│ │   └ *.csv            Input sets (one file per set)
│ └ output
│   └ *.csv              Output variables (one file per variable)
├ pyproject.toml         File for installation process
└ setup.cfg              File for installation process
```

Figure C.1: File tree.

```python
import os
import boto3
import shutil

s3 = boto3.resource(service_name = 's3',
                    region_name = 'eu-west-1',
                    aws_access_key_id = *******,
                    aws_secret_access_key = *******)

bucket_in = 'pyomo-in'
bucket_out = 'pyomo-out'
data = 'data.zip'

def download_data():
    s3.Bucket(bucket_in).download_file(Key=data, Filename=data)
    shutil.unpack_archive(data)

def upload_data():
    shutil.move('data', 'data_out/data')
    shutil.make_archive(os.path.splitext(data)[0],'zip','data_out')
    s3.Bucket(bucket_out).upload_file(Filename=data, Key=data)
```

Code 2: data_S3.py: functions to interact with S3 buckets.

Once the container image is created, it is pushed (uploaded) to ECR, and then the AWS services are configured so that the interaction with the user is minimal. The simplified process from the point of view of the user is: 1) the user uploads the input data file to S3, 2) the optimization model is automatically executed and the results are stored in S3, and finally, 3) the user downloads the results. The detailed representation of how this process works is shown in Figure C.2, and explained below:

1. The user uploads data to the data entry bucket in S3.
2. A rule of the EventBirdge service detects that there are new items in the input bucket and executes an Elastic Container Service (ECS) task.
3. The ECS task creates an instance of the Docker image of the model (stored in ECR) in an ECS cluster.
4. The container connects to the S3 input bucket to download the data uploaded by the user.
5. The optimization model is run on the container.
6. Container connects to the S3 output bucket to upload model solutions.
7. The user downloads the model solutions stored in S3.

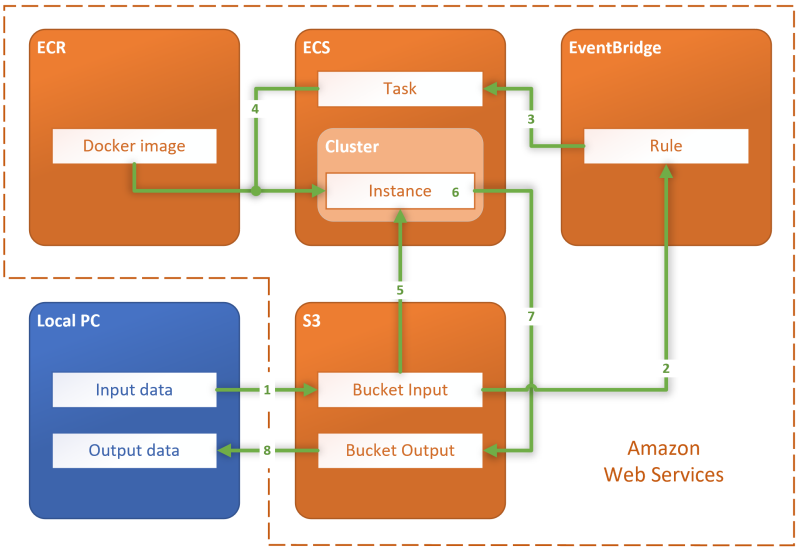


Figure C.2: Optimization process in AWS.

C.2 Docker container creation

The container image is created with docker. The steps to be performed are presented in figure Figure C.3 and detailed below:

1. Pull (download) a Ubuntu image to be used as a base.
2. Create a container using the Ubuntu image.

3. Start the container.
4. Copy the required files to the container. These files must be in the terminal's current path (`C:\docker` in the example).
   - `gams_installer.exe`: intallation file for GAMS.
   - `gasmlice.txt`: license for GAMS.
   - `GilitoDocker.zip`: the project with the optimization model presented in Figure C.1.
   - `installer.sh`: script to install everything needed inside the container.
5. Open a terminal in the docker using the interactive mode to execute commands inside the container.
6. Execute the script `installer.sh`. This script, shown in Listing 3, performs the following operations:
   (a) Unwraps the compressed version of the Ubuntu docker image to allow more commands.
   (b) Installs a tool to decompress files.
   (c) Gives executable permissions to `gams_installer.exe`.
   (d) Executes `gams_installer.exe` to decompress it.
   (e) Moves the GAMS license to the GAMS directory.
   (f) Installs GAMS.
   (g) Changes the Ubuntu repositories to point the Ubuntu version that has python version 3.8.
   (h) Updates repository sources inside the system.
   (i) Installs python 3.8.
   (j) Decompresses `GilitoDocker.zip`.
   (k) Enters the project main folder.
   (l) Installs the python virtual environment package.
   (m) Creates a python virtual environment specific for the project where all packages are going to be installed.
   (n) Activates the virtual python environment.
   (o) Installs all the packages needed for the project (`pyproject.toml` and `setup.cfg`).
7. Exit the interactive mode of the container.
8. Stop the container.
9. Commit (save) the status of the container to a new image.

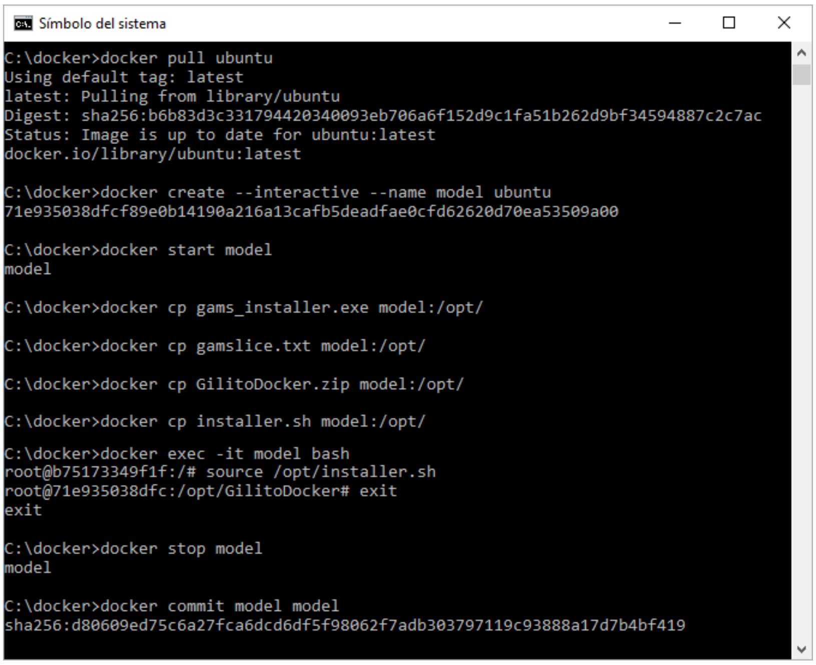


Figure C.3: Docker image creation.

```bash
#!/bin/bash
yes | unminimize
apt install unzip -y
cd /opt
chmod +x gams_installer.exe
./gams_installer.exe
mv gamslice.txt gams34.3_linux_x64_64_sfx/
cd gams34.3_linux_x64_64_sfx/
./gamsinst < /dev/null
cd ..
sed 's/jammy/focal/g' /etc/apt/sources.list > sources.list
mv sources.list /etc/apt/
apt update
apt install python3.8 python3-pip -y
unzip GilitoDocker.zip
cd GilitoDocker
pip install virtualenv
virtualenv venv
. venv/bin/activate
pip install -e .
```

Code 3: installer.sh: docker setup.

C.3 Amazon Web Services setup

The AWS services' setup to configure the automatic model execution consists of thirty-eight steps. A visual guide is presented where each step is described in the corresponding figure caption to ease the following of the steps. For this specify guide, all captions are placed on top of the figures.

Figure C.4: AWS setup step 1: Open the ECR service.

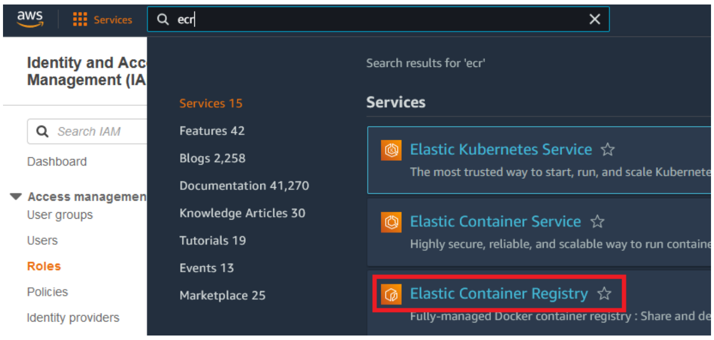


Figure C.5: AWS setup step 2: Ensure that the correct region is selected.

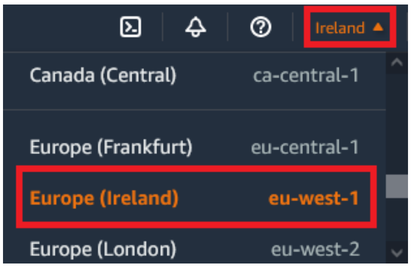


Figure C.6: AWS setup step 3: Create a new repository.

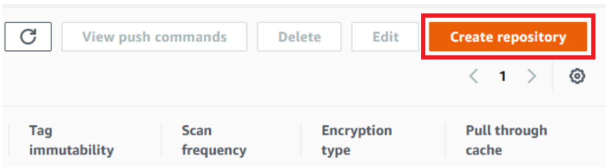


Figure C.7: AWS setup step 4: Mark the repository as private and introduce name for it.

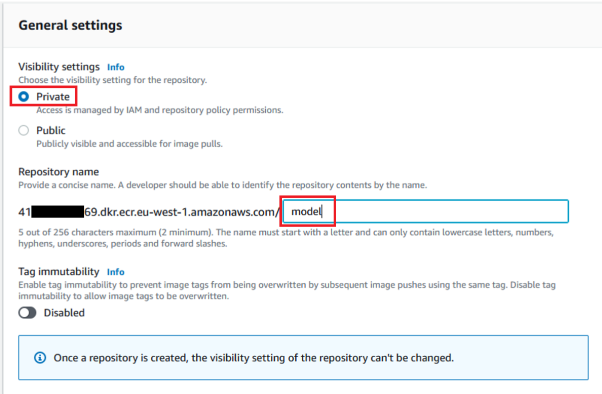


Figure C.8: AWS setup step 5: Create the repository.

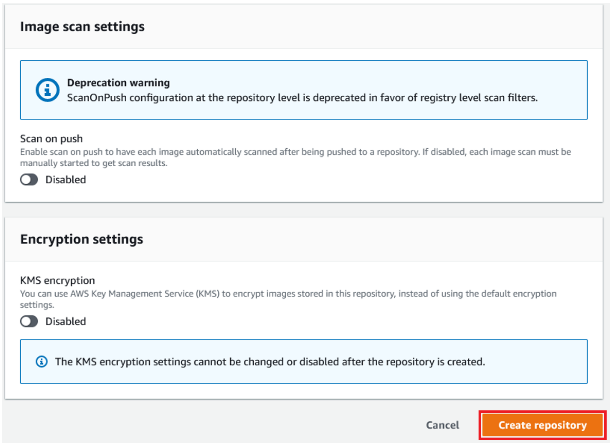


Figure C.9: AWS setup step 6: Select the repository that have been created and click in View push commands.

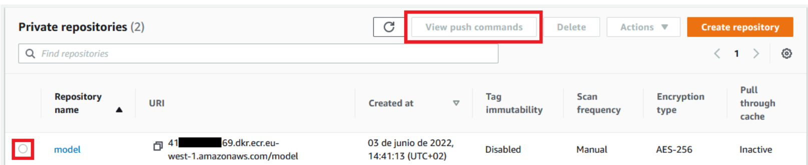


Figure C.10: AWS setup step 7: Copy the instructions needed to push the docker container image to the AWS repository.

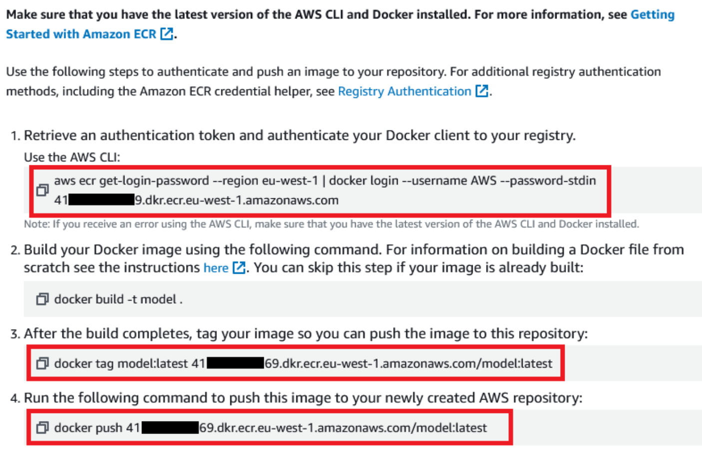


Figure C.11: AWS setup step 8: Open a terminal (CMD in Windows) and introduce the instructions from the previous step: 1) log into the AWS repository, 2) rename the container image with the name that the repository expects, and 3) push the image to the AWS repository.

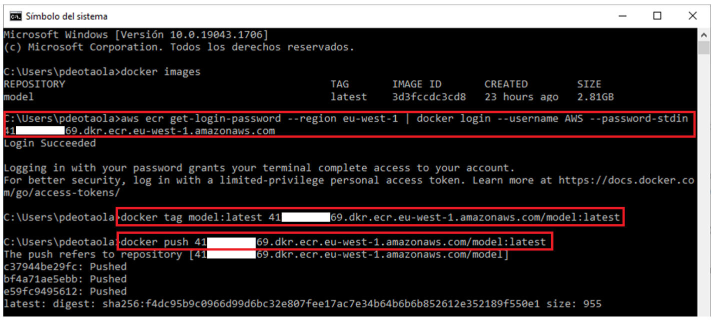


Figure C.12: AWS setup step 9: Open the S3 service.

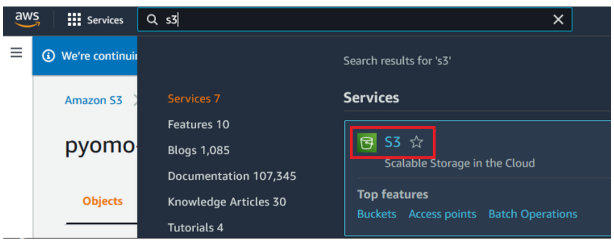


Figure C.13: AWS setup step 10: Create a new bucket for the model input data.

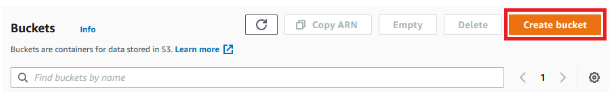


Figure C.14: AWS setup step 11: Introduce a name for the bucket and select the region.

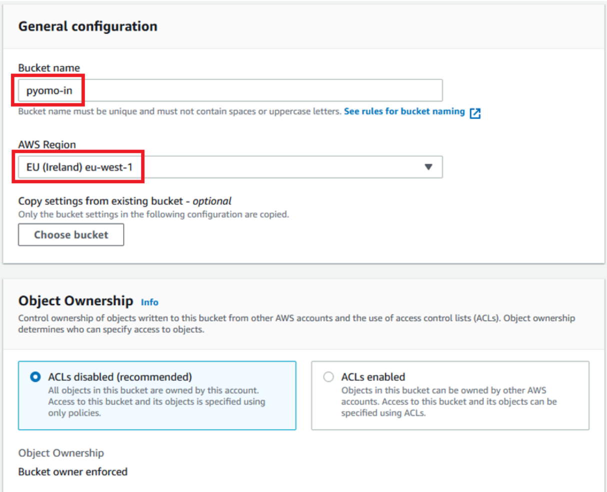


Figure C.15: AWS setup step 12: Repeat the previous steps to create a second bucket for the model output. The resulting two buckets should look like this.

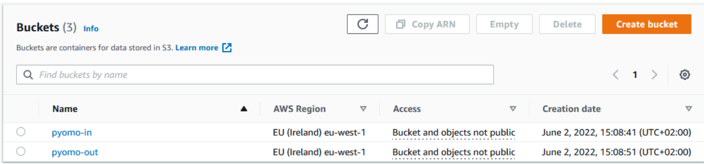


Figure C.16: AWS setup step 13: Open the Identity and Access Management (IAM) service.

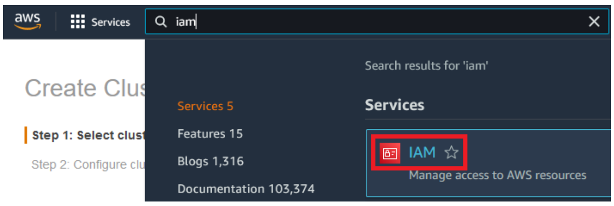


Figure C.17: AWS setup step 14: Create a new role.

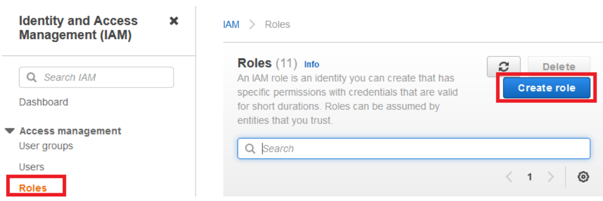


Figure C.18: AWS setup step 15: Select the AWS service, search for Elastic Container Service and select the Elastic Container Service Task.

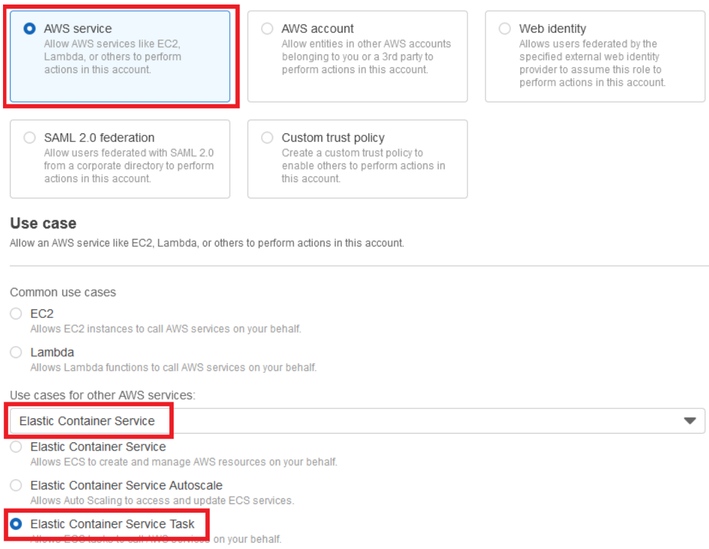


Figure C.19: AWS setup step 16: Specify a name for the role.

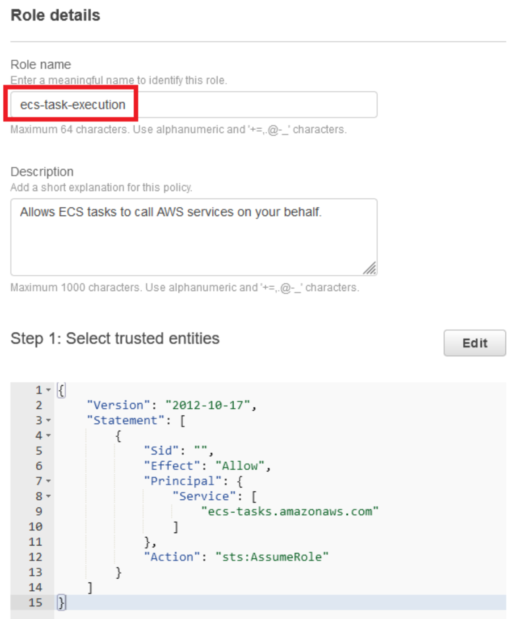


Figure C.20: AWS setup step 17: Open the ECS service (and select the region as in Figure C.5).

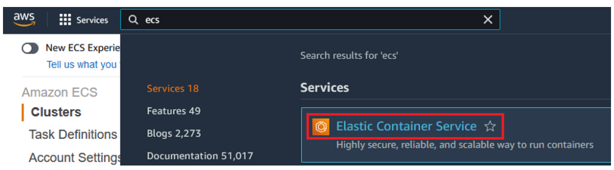


Figure C.21: AWS setup step 18: Create a new cluster.

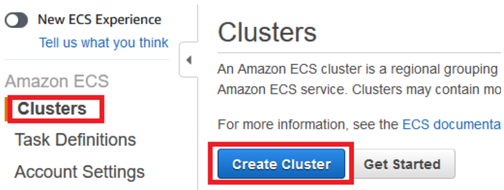


Figure C.22: AWS setup step 19: Select the Networking only option.

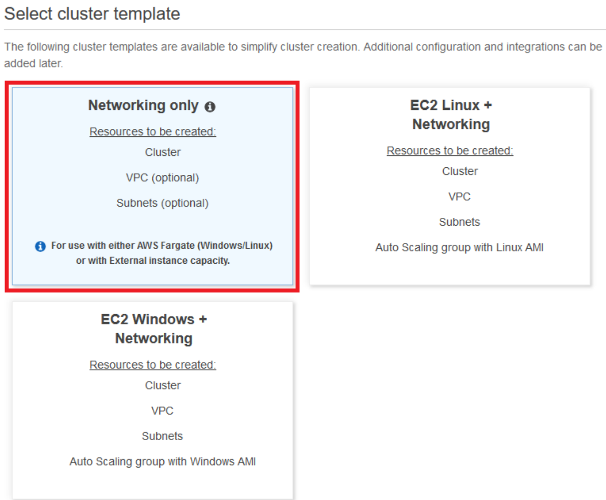


Figure C.23: AWS setup step 20: Specify a name for the cluster, check the Virtual private Network (VPC) (to create a network), and CloudWatch (to enable the logging) check-boxes.

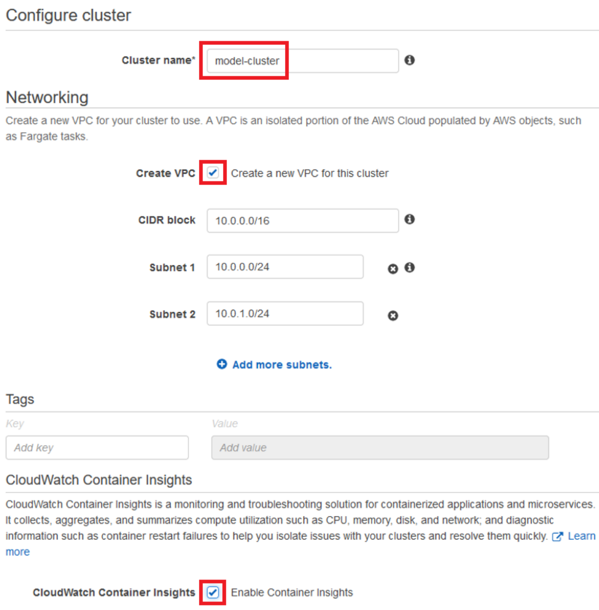


Figure C.24: AWS setup step 21: Create a new task.

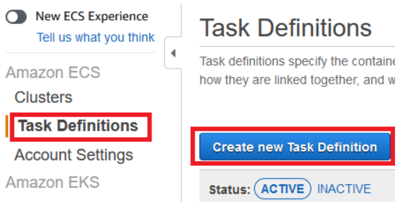


Figure C.25: AWS setup step 22: Select the Fargate Option.

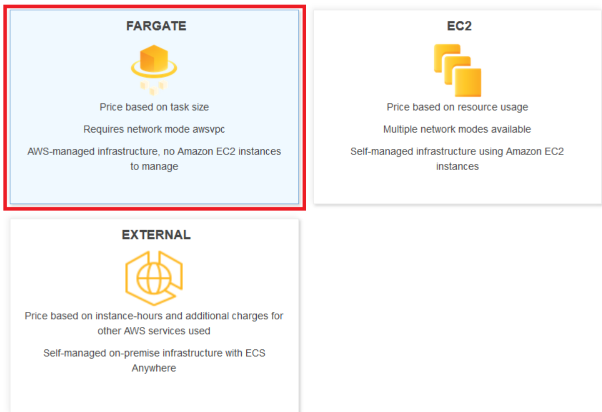


Figure C.26: AWS setup step 23: Specify a name for the task, select the previously created role as task role, Linux as OS and ecsTaskExecutionRole as task execution role.

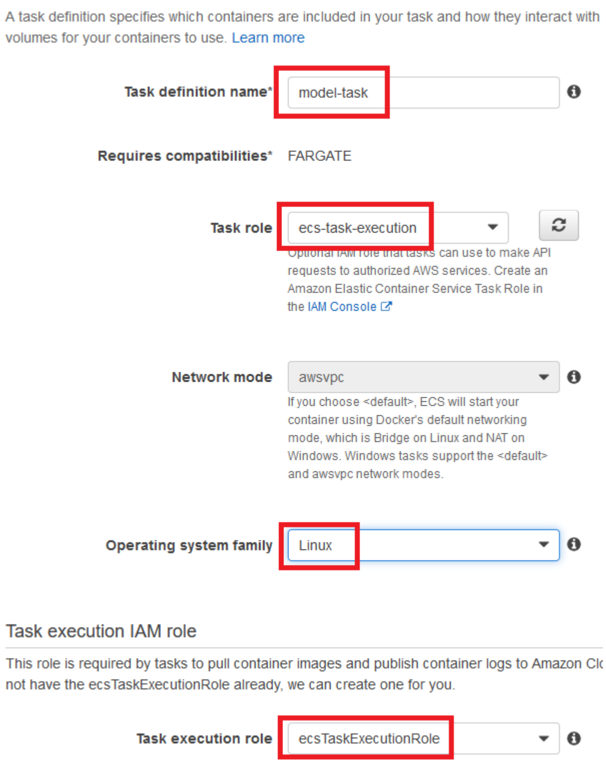


Figure C.27: AWS setup step 24: Select the amount of memory and the number of CPUs, and click in add container to select the container settings.

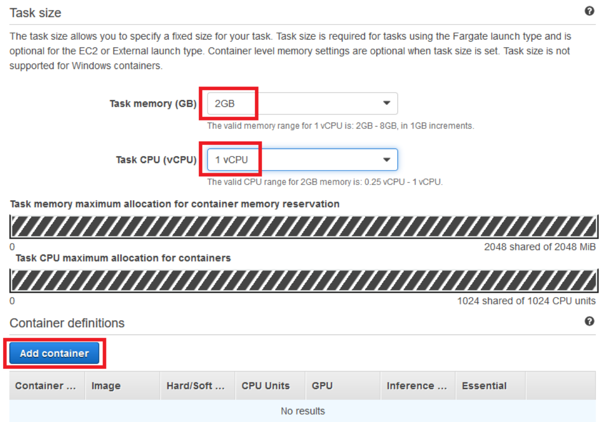


Figure C.28: AWS setup step 25: Specify a name for the container and the image (that has to be the name of the image in the ECR. Although the repository is private it is hosted in AWS own repository, therefore the private repository check-box should be empty.

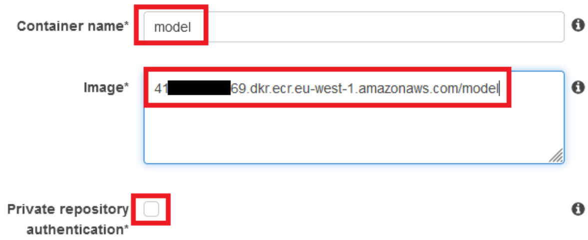


Figure C.29: AWS setup step 26: Introduce the entry point, command, and working directory. The commands perform three operations: 1) include GAMS in the system path, 2) activate the python virtual environment, and 3) execute the python script that runs the optimization model. The entry point is the main directory of the model.

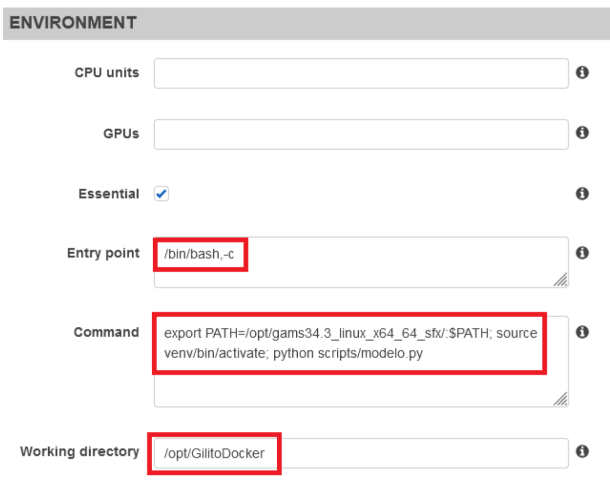


Figure C.30: AWS setup step 27: Select the task that has been created and click in run task to try it.

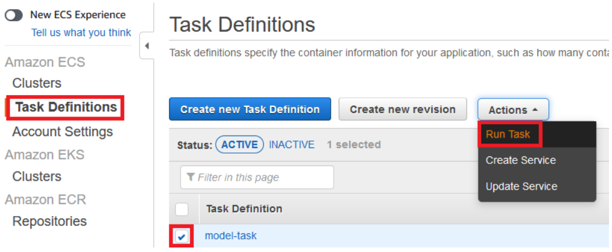


Figure C.31: AWS setup step 28: Select the options Fargate and Linux, and choose the cluster created in Figure C.21.

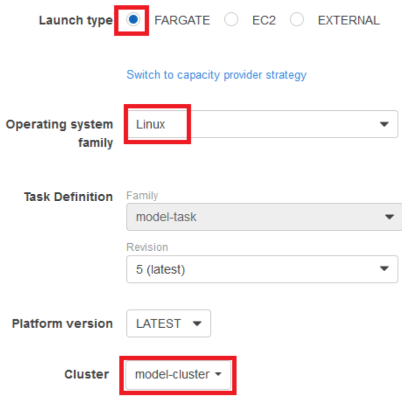


Figure C.32: AWS setup step 29: Select a subnet and security group.

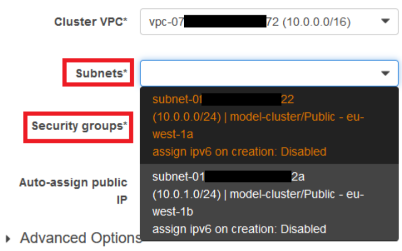


Figure C.33: AWS setup step 30: The first time select Create new security group, and for further executions select a existing security group. Note that the security group ID will be needed to configure the automatic execution.

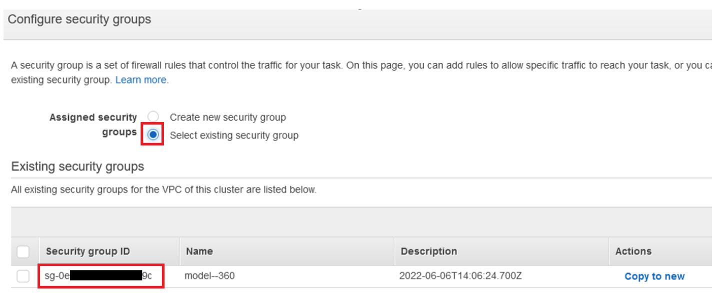


Figure C.34: AWS setup step 31: Open the Amazon EventBridge service (and select the region as in Figure C.5).

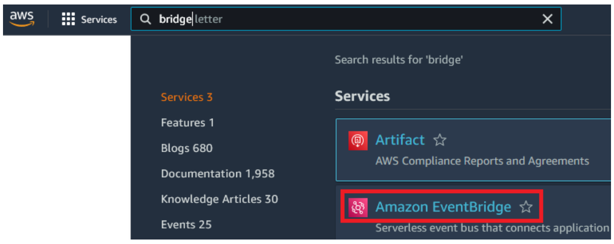


Figure C.35: AWS setup step 32: Create a new rule.

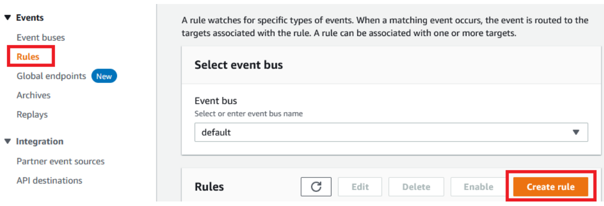


Figure C.36: AWS setup step 33: Specify a name for the rule and choose the event pattern option.

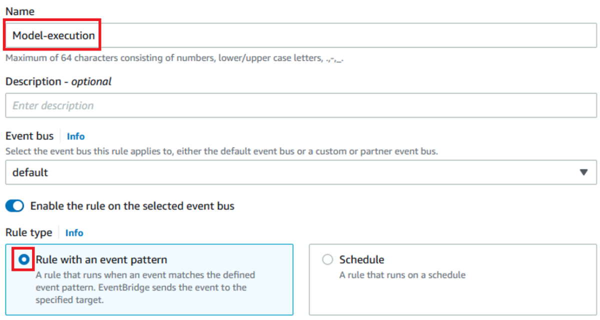


Figure C.37: AWS setup step 34: The source of event is a AWS event.

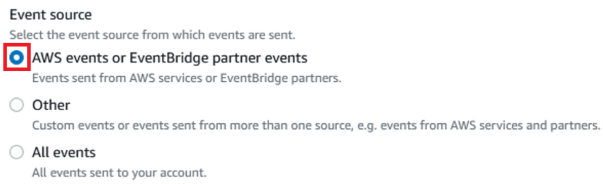


Figure C.38: AWS setup step 35: Choose the following options to indicate that the execution should be triggered when a new object is created in a bucket, and specify the name of the bucket created for the model input data in Figure C.13.

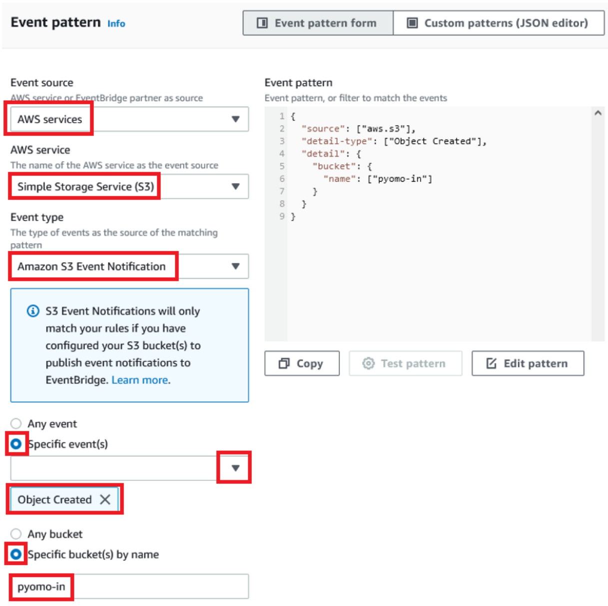


Figure C.39: AWS setup step 36: Select a ECS task as target task to be execute, and specify the name of the task and cluster created in Figure C.24 and Figure C.21.

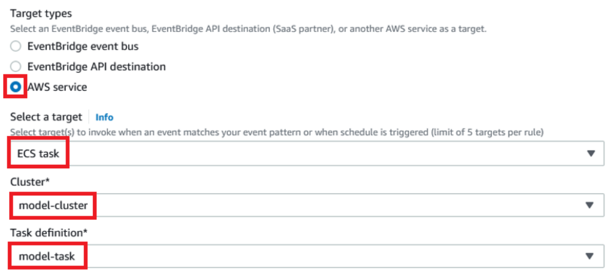


Figure C.40: AWS setup step 37: Select Fargate as launch type, and specify the subnet and security group from Figure C.32 and Figure C.33.

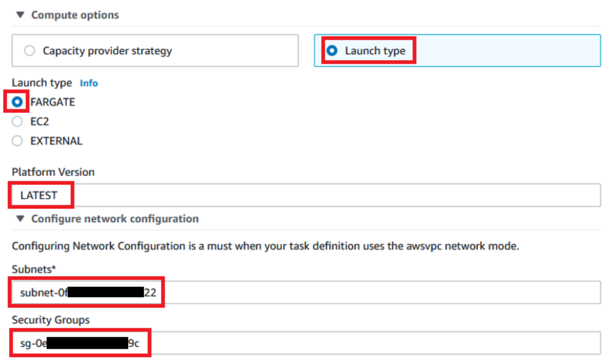
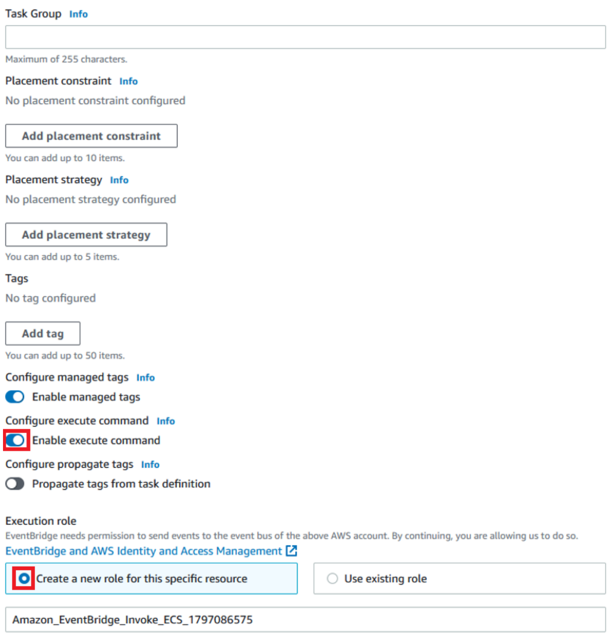


Figure C.41: AWS setup step 38: Enable the execution command and create a new role for the resource.



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