INSTITUTO DE INVESTIGACIÓN TECNOLÓGICA

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STEXEM

Task 2: Long-Term Models for Integration of RE Technologies

S. Wogrin, I. González-Romero, D. Tejada-Arango, J. J. Valentín, T. Gómez, E. Centeno

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Santa Cruz de Marcenado, 26. 28015 Madrid (Spain). Tel +34 91 542 28 00. Fax +34 91 542 31 76

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CONTENTS

1 Long-Term Models for Integration of RE Technologies

In this task we investigate in depth the generation and transmission expansion planning problem. For this purpose, in Section 2 we present a complete literature review on this capacity expansion problem. In Section 2.1, we present the current models and literature gaps on traditional co-optimization (cost minimization) problems and, in Section 2.2, we do the same for the co-planning equilibrium models that consider the introduction of game theory into this capacity expansion problem. In Section 3 we develop the formulation of the well-known cost-minimization problem that is currently used by the vast majority of TSOs in the world. We present both the deterministic version in Section 3.1 and we present a comparison of diverse scenario based methods to represent wind uncertainty in Section 3.2. Additionally, in Section 4, we formulate the our co-planning equilibrium problem and its properties. In Section 4.1 we present the notation used along the whole Section4 . In Section 4.2 we introduce the novel bi-level generation and transmission expansion planning model. The latter accounts for the fact that both generation expansion and operational decisions are made by distinct profit-maximising GENCOs with different objectives from those of a welfare-maximising TSO. In Section 4.3 we compute the social welfare loss of implementing a cost-minimization model used by TSOs, instead of our proposed approach that allow us to internalise strategic interactions in electricity markets. Finally, in Section 5, we introduce the bi-level generation and transmission expansion planning under uncertainty, we define the stochastic model and a min-mar regret bi-level model, we develop a case and we show some illustrative results.

2 Review on generation and transmission expansion co-planning models under a market environment

Power systems were conventionally structured under a *centralised environment*, where a cost minimising vertically-integrated utility was in charge of deciding, among other matters, both transmission expansion planning (TEP) and generation expansion planning (GEP). However, due to computational limitations, in the past TEP and GEP were usually solved as independent problems. A great amount of research has been published on both separately, with the focus shifting recently to contemplating bigger networks, more detailed operation of conventional units, renewable generation, batteries, distributed generation and their corresponding support schemes. For a complete review of these separate problems please refer to [1].

With the development of computational capability, the joint consideration of TEP and GEP became possible, allowing to jointly consider the important links between generation dispatch and transmission supply along with their siting and sizing decisions. These models, usually known as generation expansion planning and transmission expansion planning co-optimisation models (GEPTEP co-optimisation models), take into consideration the links between generation and transmission, resulting in a lower system cost compared to a separate GEP / TEP optimisation approach, as shown in [2]-[5]. This cost minimisation framework is equivalent to maximizing the total welfare of the system when three assumptions are made: i) perfect competition, ii) simultaneous operating and investment decisions, and iii) perfect information. However, this co-optimisation framework does not address sequential and strategic decisions that emerge in a decentralised *market environment*.

The vast majority of power systems today are structured in a liberalised market, in which private companies compete with each other (in generation and retail). Therefore, the investment and operation decisions in this *market environment* are quite different from those in a *centralised environment*. In a liberalised market, generation expansion and operation are decided in a competitive way where every generation company (GENCO) makes its own decisions aiming to maximise total profits, while the transmission planning keeps being centralised. In this sense, the liberalisation of electricity markets has introduced new dynamics that lead to conflicting interests between the different decision makers in the electric power system. The behaviour of GENCOs can be modelled by means of game theory to represent their strategic interactions as a Nash equilibrium. Moreover, if we consider the sequence between investment and operation for these strategic agents, hierarchical models (bi-level) allow us to represent such structures. Bearing this in mind, hierarchical equilibrium models represent an adequate tool to study how different agents in GEPTEP problems behave under a market environment.

Once the context is set, we can move on from the term "*co-optimisation*" to the more accurate "*co-planning*". We introduce this term, given that these models do not address, in essence, a single optimisation problem. Thus, *co-planning models,* help us to understand how Transmission Companies (TRANSCOs) and Generation Companies (GENCOs) take strategic and sequential decisions. For example, consider the case where transmission expansion decisions are made first, and subsequently, under a market framework, GENCOs make their expansion decisions. In this sense, equilibrium models, in particular, bi-level or multi-level problems help us model this kind of interactions.

It is important to note that strategic behaviour does not only occur in operation but also in investment decisions. This is particularly true nowadays because of the shorter construction span of generation units (mainly for renewables technologies) and longer times for transmission lines (because of stricter environmental restrictions or more demanding communities) allow GENCOs to site their units strategically in such a way that they induce congestions in the network, leading to higher operational incomes for GENCOs. This review aims to present an overview of the current state of GEPTEP models: In Section 2.1, the classical network and generation modelling are presented. We update the references presented in [3] for co-optimisation models and we extend it to the co-planning models. In Section 2.2, the properties of co-planning models and their solutions are analysed. As a novelty, we classify hierarchical GEPTEP papers based on their general hierarchical structures and sequential decisions.

Therefore, we contribute to the relevant literature by classifying both the hierarchical structure and the solution techniques of the co-planning models, offering a direct comparative of co-planning models based on consistent parameters. Additionally, we describe and classify the most commonly used techniques to solve equilibrium models, and we consider the different investment and operation modelling options and their impact on both the equilibrium structure and the type of mathematical problem. Lastly, in Section 0 we conclude.

2.1 GEPTEP modelling approaches

There are two general approaches to GEPTEP modelling. On the one hand, GEPTEP models can be used to assess national and regional energy issues (including transportation, electricity or gas sectors) to provide guidelines to policy makers. Some examples of such policy-oriented models are: MARKAL/TIMES[1] [5] , NEMS[2] [6] and IPM[3] [7]. More recently, [8] conducted a detailed comparison of US policy analysis models, including: [7], [6], [9] and [10]. On the other hand, there are some GEPTEP models focus more closely on the electricity sector and, therefore, offer a more detailed representation of technical constraints. In this group, the REEDS[4] model is worth noting [9]–[17], [18]–[23] ,[24].

When discussing GEPTEP models in general, it is important to understand how they represent the complex reality of the decision-making process in mathematical format, as modelling simplifications can potentially have a great impact on model results. The purpose of this Section is to point out the most important modelling questions in GEPTEP models, and to discuss the pros and cons of different modelling approaches. The remainder of the Section will discuss what we consider to be the most important modelling topics. The representation of the transmission network in GEPTEP models in Section 0. The representation of generation investment and operation in GEPTEP models in Section 0. How to deal with end effects regarding the temporal horizon in Section 0. How to reduce the model size by employing size reduction techniques to the network and the time horizon in Section 0; and finally, how deal with the most recent developments in the field, with the representation of storage and renewable technologies along with the uncertainty GEPTEP models in Section 0.

[1] Market Allocation developed by US International Energy Agency.
[2] National Energy Modeling Systems developed by the US Energy Information Administration
[3] Integrated Planning Model by US Environment Protection Agency
[4] Regional Energy Deployment System developed by the National Renewable Energy Laboratory

Please note that this discussion is aimed at providing the necessary background on basic modelling issues in the GEPTEP realm, which will be fundamental to understand the subsequent analysis of Section 2.2. Let us now analyse the modelling topics previously pointed out, and extend the work of [3] by classifying the relevant works in the literature according to each modelling category. This classification, as well as an updated list of references on co-optimisation models are presented in Table ITable I: Classification of co-optimisation models according to their modelling approaches

. Please note that the same modelling categories are presented in co-planning models, however, given that we classify some additional features of co-planning models they are presented separately in Table V (see Section 2.2).

Network Representation

The way the network is represented is a key issue for TEP and, as a consequence, for GEPTEP problems. The transmission network is usually represented as a pipeline (the most simplified approach), as a DC lossless network (the most used approach) or as an AC network (the most accurate approach). In the case of the transportation model (also known as transhipment or pipeline), the network is represented by pipelines in which the flows can be decided ignoring the physical laws that govern power flows in an electrical network. In several long-term models [5], [9], [6] [12], the network is represented in such a way because its mathematical formulation is very simple and linear. Apart from having an overly simplistic network representation, these models also consider continuous transmission investment variables (by disregarding investment lumpiness[5]), which allows them to solve large-scale systems, while remaining under a linear formulation.

Conversely, in order to successfully represent the lumpiness of transmission investment, binary variables should be used. For instance, authors of [25] claim that a transhipment model with binary decisions approximates well real operation. This is shown in [26] by comparing a DC model with binary investment variables versus both a DC model with continuous investment and a transportation model with discrete investment variables. Authors in [26] show that, for a 2%-11% renewable portfolio standard target, disregarding lumpiness creates more distortion than disregarding a DC network approximation. However, given that a lossless DC approximation would be a better approximation (while still maintaining linearity), it is found that most of the existing detailed transmission planning models implement it. Additionally, we can also find TEP models that consider DC network losses [27], however they have not been applied to mathematical-based GEPTEP problems. In particular, some heuristics models such as [28] have considered DC losses in their planning frameworks.

Finally, the AC power flow is the most accurate representation of the network, even though it includes highly nonlinear constraints that yield more complicated models such

[5] Lumpiness of investments refers to the discrete nature of the investment decisions, for instance, half transmission line cannot be built

as MINLPs. Some linear approximations have been applied to the AC-TEP problem. Authors in [29] and [30], propose a non-scalable linear approximation that reaches a global optimum under certain conditions.

Table I: Classification of co-optimisation models according to their modelling approaches

References		[4]	[5], [7]	[9]	[11]	[12]	[13]	[14]	[16][17]$_1$	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]
Year		2012	2009	2012	2016	2012	2016	2011	2018/19	2015	2018	2014	2017	2013	2018	2017	2017
Network Represent. Model	Pipe line		X	X		X	X										X
	DC	X			X			X		X	X	X	X	X	X		
	AC								X							X	
Network Investment	Binary	X			X	X	X	X	X	X	X	X	X	X	X	X	
	Integer																X
	Continuous		X	X													
Generation Investment	Binary	X		X	X	X	X	X	X	X	X	X		X	X	X	
	Continuous		X										X				X
End Effect	Rec./Pres Value							X				X		X	X		
	Annual. Value	X	X	X	X	X	X		X	X	X		X			X	
	Extended Period																X
Time Represent.	Load Level.	X		X	X	X	X	X	X	X	X	X		X	X	X	X
	Represent. Periods		X										X				
Dynamicity	Static	X		X			X	X	X	X	X	X			X	X	X
	Dynamic		X		X	X							X	X			
Storage Modelling	Short Term	X	X	X		X*[6]				X			X	X*	X*		
	Long Term		X[7]	X*		X									X		X
	None				X		X	X	X		X	X				X	
Uncertainty	Deterministic	X	X	X	X	X	X		X		X[8]		X		X	X	X
	Probabilistic											X		X[9]			
	Stochastic								X$_1$	X							
Test System		Brazil-46	Flex[10]	Flex	Zonal-5	WECC 50	EI-25	Garver-6	IEEE-24	IEEE-14	IEEE-118	IEEE-118	IEEE-24	IEEE-118	Chile-27	IEEE-118	EI[11]-24

*6 Energy balance or hydro storage is simplified
7 Simplified storage operation
8 Load levels are considered as scenarios
9 It is done with and ex-post probabilistic simulation.
10 Comercial softwares with flexible input data
11 Eastern Interconection

Additionally, authors in [31] propose a piece-wise linear approximation that proves global optimality for small instances, but only feasibility for large instances. Some other techniques have been developed, such as Second Order Cone Programming (SOCP) and Semidefinite Programming, that formulate convex approximations for the AC power flow [32],[33]. In fact, [16], [17] and [24] propose an AC GEPTEP co-optimisation problem including a second order relaxation of the AC power flow.

Authors in [24] and [16] show that CPU time decreases up to 10 times compared to the traditional mixed integer conic programming. It is important to note that AC formulation makes possible to integrate FACTs[24] technology in the co-optimisation problems by assessing the load shedding caused by reactive power [17]. We would like to emphasize that all the manuscripts reviewed on GEPTEP co-planning (see) consider a DC power flow network representation (which implies that the only difference between co-planning models is whether transmission investment is binary or continuous). In particular, in [34] the application of an AC power flow for a bi-level model in the context of TSO-DSO coordination is implemented. This framework can be used as reference for future research on how to represent the AC network in the co-planning context.

Generation Representation

The aspect of the representation of generation and generation expansion that interests us here is the use of binary or discrete variables. While using discrete variables instead of continuous ones might represent reality more accurately in many cases (i.e., investment decisions, start-up/shut-down decisions), it also greatly impacts the computational complexity of the resulting GEPTEP model. In general, the representation of unit commitment constraints is not included in GEPTEP problems mainly due to CPU limitations. To the best of our knowledge only [21] has considered a detailed UC formulation. Additionally, in terms of investment decisions, generation expansion can be modelled either as continuous variables [7] and [26] integer variables like the approach followed by [13], [25] and [14], or as binary decisions like in [22]-[35]. The alternative of using continuous variables instead of binary variables decreases the search space and computation time, but it reduces model accuracy. However, given that economies of scale in generation are much lower than in transmission investment, generation lumpiness can be sometimes disregarded. Therefore, under certain circumstances, the binary generation investment variables can be relaxed [36] and finally adopt different rated capacities for each generator and achieve accurate results. More recently, some reliability models have been developed to tackle units’ availability. These models are solved either by optimisation [20],[19] or by meta-heuristics [37][26].

End Effect

As a consequence of computational limitations, the planning horizon for GEPTEP models is usually lower than the real lifetime of generation and transmission assets. Consequently, in GEPTEP models, the value in use of the investments can be usually distorted at the end of the planning periods. Therefore, modelling investment recovery is a key point in generation and transmission expansion planning approaches. This issue can be solved by including recovery values for the assets at the end of the study horizon as shown in [38]. Additionally, an extended simulation can be run as shown in [25], where authors consider a 40 years horizon by duplicating the results of the first 20 years of operation.

The annualised value of investments can be implemented to internalise the value of money over time, as shown in [18]. For a multiyear model, the annual value of investments contemplates not only the value of money, but also the optimal building time of the facilities, (as opposed to static approaches). All these approaches have some pros and cons, as shown in [39]; either choice represents a trade-off between the CPU time and accuracy. However, among the papers reviewed here (see Table I), modelling an annualised value is by far the most used option, because it easily introduces the value of money over time in the whole optimisation horizon.

Finally, it is important to note the mathematical-based algorithms usually consider a single target year because they are not suitable for large-scale problems. Consequently, most of the work done for multi-year programming has been tackled with some alternative metaheuristics algorithms [28]. However, recent advances in computational speed, by properly considering the most relevant assumptions, has allowed to tackle the multistage programming as seen in [21], making possible to determine not only the optimal siting, but also the optimal time of construction of the investments. Additionally, the advancements in algorithms to represent uncertainty, that also consider large scale problems (see Section 0), have also permitted to tackle the multistage programming [40].

Size Reduction Techniques

Long-term models have to deal with the trade-off between the representation of short-term operation constraints and the representation of long-term investment decisions. This implies that hourly operating constraints cannot be retained for several years in a large system because the model becomes computationally intractable. This concern has increased because of the high penetration of renewable technologies, that make the impact of ramping constraints, and the capability of storage technologies to balance them, more relevant.

Consequently, current research is focused on reducing either the network size or the time steps representation. The actual transmission network can be reduced so that an equivalent resulting network renders the same or approximate solution. Some of these techniques [41]–[44] have been applied only for TEP problems. On the other hand, time-steps can be reduced by, for example, using load levels or representative days. As seen in Table II , most of the models used a traditional load level approach and only few of them used a representative periods approach.

In general, detailed clustering approaches for time reduction [45]–[48] are proposed for GEP problems when intraday constraints are needed to be modelled, as in the case of battery operation. However, only some of these techniques have been applied to GEPTEP problems. For instance, authors in [23] applied a load level approach with a square-mean-error clustering technique in a GEPTEP problem with batteries deployment. Additionally, they characterise wind and solar availability profiles of each hour before clustering load levels, but they disregard transitions between clusters. Some of these techniques have been applied to GEPTEP co-planning problems, as it will be discussed in 0.

Most recent developments

The major recent developments in GEPTEP have been the introduction of renewables generation, which brings along a high uncertainty in renewables resources, and the utilisation of storage technologies that help manage the intermittency introduced by renewables.

Uncertainty Representation

There are multiple sources of uncertainty for GEPTEP problems; some of them are long-term uncertainties such as climate variables (i.e. hydro seasons), fuel availability, and demand growth; some are short term, such as: daily weather for renewables, units availability, daily demand, and transmission capacity factor. The representation of uncertainty was initially approached by probabilistic methods, in which the availability of either generation units or lines is simulated to take into account reliability measures [14], [20]. Later, stochastic programming has been considered in a few cases [21],[17] applied to the traditional co-optimisation model. Finally, other techniques such as robust optimisation have appeared, mainly applied to co-planning models in a market environment context, as will be discussed in Section 0.

Storage Modelling

Co-optimisation of transmission and storage investments can be found most notably in [21] and [18] both studies achieve a lower cost system compared to a separate optimization. Energy Storage Systems (ESS) sizing and siting optimisation are also presented in [49] and [50]. Authors in [49] demonstrates that the conditions of siting are dependent on the type of ESS technology; [50] concludes that a minimum profit constraint should be included in order to guarantee recovery of investment. Additionally, authors in [4] show that investment in ESS reduces transmission investment costs. In [51], authors consider ESS and a DC transmission losses approximation, the conclusion is that ESS reduce transmission costs and add flexibility to the system. The general inference of the previous studies is that ESS are a substitute of transmission, however, authors in [23] show that ESS can also be complementary to transmission, depending on the system characteristics and the level of distribution of the ESS deployment.

Modelling Approaches Gaps

Authors in [8] research the challenges for renewables generation modelling in policy analysis models, and compare results for a US study case. They conclude that active areas for modelling enhancement are i) spatial and temporal resolution, ii) resource adequacy, and iii) economics of energy production. Additionally, lower times of constructions for renewable generation (wind, solar), and longer construction time for transmission allow GENCOs to exercise more market power in response to transmission siting, making the analysis of strategic decisions more relevant. Finally, considering strategic reactive power in the co-planning problem could help reduce load shedding and overall cost of the system, through joint allocation of transmission lines, conventional units, and reactive power sources [17].

2.2 Co-planning equilibrium models

In this Section, we present a literature review on equilibrium co-planning GEPTEP models (as opposed to *co-optimisation* models) with a particular focus on multi-level models. We will consider four different categories in the analysis of co-planning GEPTEP models: equilibrium structure, regulatory framework, solution techniques, and the most recent development on modelling of storage and uncertainty in a market environment. We will provide a detailed literature review and a classification of the existing equilibrium GEPTEP models, as well as the individual discussion on each category. In Section 0, we classify the different GEPTEP co-planning models depending on their equilibrium structure. In order to do so, we first introduce market-only (no investment) equilibrium models, as they usually constitute the lower level of multi-level co-planning models. We then present the possible different structures of equilibrium models and we classify co-planning models accordingly.

In Section 0, we examine the possible regulatory frameworks where co-planning GEPTEP models are applied, and the corresponding hierarchy of decisions and degree of competition considered. Section 0 explores the most common solutions techniques for hierarchical equilibrium models and classifies the literature in the corresponding categories. Finally, Section 0 contains a review of storage and uncertainty approaches under a co-planning market framework. Figure 1 summarises the properties of GEPTEP co-planning models explored in the whole Section 2.2.

Equilibrium Structure

When discussing the equilibrium structure of GEPTEP models, several different cases have to be considered, as depicted in Figure 1.

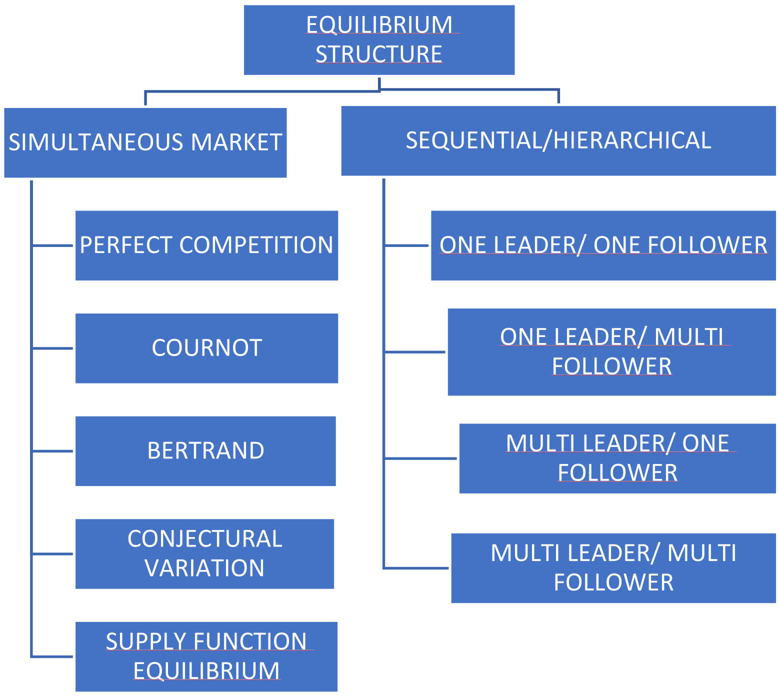


Figure 1: **General Mathematical Structure of Equilibrium Models**

The first distinction is whether the nature of the game is simultaneous or sequential. Simultaneous games, are equilibrium structures where all decision variables are assumed to be taken simultaneously, i.e., TEP investment, GEP investment, and market operating decisions happen all at once. In a sequential or hierarchical structure, one set of decisions is taken before the other in a Stackelberg manner. Section 0 introduces simultaneous equilibrium models, both market and co-planning. In Section 0 we continue with sequential equilibrium markets and conclude with the characterisation of sequential co-planning models.

Simultaneous One-Level Structure

We present simultaneous market models, to then cite some simultaneous co-planning models, despite the latter being scarce in the literature (given that co-planning models are usually more interesting when studying the sequence between investment and operation decisions).

Simultaneous Market Models

There exists a wide range of research on simultaneous equilibrium models that simulate the electricity market functioning, mainly to represent oligopolistic behaviour among decentralised GENCOs. In this sense, the following modelling approaches are usually studied: a) Perfect Competition: no market power, b) Cournot: firms decide on quantity, c) Bertrand: firms decide on price, d) Conjectural variations: a generalisation that, over a “conjecture”, can result in models a) & b), and e) Supply Function Equilibrium (SFE): firms decide a price-quantity bid. A description of simultaneous equilibrium models applied to electricity markets when network is disregarded, is shown in [52]. Additionally, a review of Oligopolistic Network-Constrained Models (ONCM) is presented in [53]. The seminal paper on ONCMs by Hashimoto [54] introduces the network equilibrium model to study systematically the oligopolistic behaviour of producers in a simplified transportation network. Under this framework, we identify two decisions makers: GENCOs and ISO (or TSO). It is important to distinguish the two main features that affect the way prices are created in ONCMs (please refer to Table III for the summary):

a) GENCOs reaction to transmission prices. As shown in [55], even if generation operation is competitive, GENCOs can exercise market power if transmission rights are passive. As an alternative, authors in [55] propose a parallel market for transmission rights that affects generators bids and leads to optimal pricing. Subsequently, in [56] and [57], the authors consider two different ways for modelling transmission prices, stamp (uniform) and marginal prices. This is obtained by considering that GENCOs react *a la Cournot* to transmission prices. Authors claim that multiple equilibria can arise under stamp pricing; while uniqueness can only be guaranteed for marginal.

b) Nodal Price Difference: A concern with previous models [55]–[57] is that difference in nodal prices might not necessarily be explained by GENCOs marginal costs. [58] proposes adding an arbitrager to the network. With this in mind, [58] proposes solving the *bilateral* market with a quadratic optimisation problem (that copes with large scale systems). Under this framework, GENCOs compete *a la Cournot*; while they react to transmission prices *a la Bertrand* (GENCOs cannot affect transmission prices). Author in [58] also shows that a bilateral market with an arbitrager is equivalent to a POOLCO market (where players react *a la Cournot* to transmission prices).

Simultaneous Co-planning Models

As mentioned before, our search only found two papers that deal with simultaneous co-planning models. On one hand, authors in [56], model both transmission and generation expansion planning. However, computation limitation at the time of publication prevent the study of a real size model. Additionally, in [35] authors formulate an equilibrium model to study the strategic interactions between TRANSCOs and GENCOs; then they transform the resulting Mixed Complementarity Problem (MCP) to a Quadratic Programming Problem (QPP), allowing them to solve big size problems. While a simultaneous decision-making structure leads to simpler models, it is also a simplification of reality, that can potentially lead to a distortion of optimal planning results.

Hierarchical Multi-level Structure

Contrary to simultaneous games, sequential games model a decision-making hierarchy *a la Stackelberg* [59].

*Table II: **Classification of hierarchical multilevel models***

	Leaders	Followers
OLOF	ONE	ONE
OLMF	ONE	MULTIPLE
MLOF	MULTIPLE	ONE
MLMF	MULTIPLE	MULTIPLE

Stackelberg [59] simulates a market with a leading firm and multiple followers. This game is defined as an equilibrium, where the decisions of the leader are made considering the best reaction of the followers that, simultaneously, make their decisions knowing how the leader would react anticipating their own decisions. In this sense, bi-level programming generalises the Stackelberg model by extending the number of players (and the type of decisions) in the game. Table II classifies these models following [60]. It is important to note that the different levels in a multi-level framework can be either represented by different actors (e.g. TRANSCO, System Operator or GENCOs) or by different types of decisions (e.g. investment and operation). As mentioned in Section 0, the market is generally considered as a simultaneous game, where GENCOs and System Operator decisions are taken. Nevertheless, other models consider a sequence between the decisions of GENCOs and the clearing process made by the System Operator. These models are called “Hierarchical Market Models”, and some of their properties will be discussed because they are relevant for the subsequent review of hierarchical GEPTEP models.

Hierarchical Market Models

In Table III, the main characteristics of simultaneous OCNMs (see in 0) and hierarchical OCNMs (as an alternative to improve transmission pricing) are presented. In this respect, authors in [61] extend the work on simultaneous OCNM done in [58].They propose a sequential Stackelberg model where GENCOs anticipate the TSO decisions (leader). The main contribution of [61] is to demonstrate that their proposal is a generalisation of [58]. Additionally, [62] makes a comparison of three large-scale hierarchical market models. The authors in [62] makes a comparison of the model COMPETES [63], Cambridge I, II [64] and the Madrid model [65].

*Table III: **Oligopolistic Network-Constrained Market Models Characteristics***

	TSO/ISO* Objective Function	GENCO Objective Function	Reaction to prices	Arbitrage	Structure
[55]	Maximise: Social Welfare	Maximise: Profits – TP	Cournot	NO	SIM
[56]	i)Min: Investment Cost ii) Fixed Rule	Maximise: Profits – TP	Cournot	NO	SIM
[57]	Fixed Rule	Maximise: Profits	Bertrand	NO	SIM
[58]	Maximise: Congestion Rents	Maximise: Profits – TP- ABP	Bertrand	BOTH	SIM
[66]	Maximise: Social Welfare	i) Max: Profit +Nodal Premium ii) Anticipate	i) Bertrand ii) Stackelberg	NO	i) SIM ii) SEQ
[61]	Maximise Congestion Rents + ABP	Maximise: Profits – TP- ABP	i) Cournot ii) Stackelberg	YES	i) SIM ii) SEQ
[64]	Maximise: Social Welfare	Maximise: Profits – TP	Stackelberg	YES	SEQ
[65]	Maximise: Utility	Maximise: Benefits	Stackelberg	NO	SEQ
[67]	Maximise Congestion Rents + ABP	Maximise: Profits	i) Bertrand ii) Stackelberg	YES	i) SIM ii) SEQ

SIM: Simultaneous SEQ = Sequential. TP = Transmission Price. ABP= Arbitraged Payments (nodal price x traded quantities).

Authors in [62] find that, when perfect competition is considered, production and pricing results are the same for all models. However, when oligopolistic competition is considered, pricing results might highly differ; prices could be twice as much in one case compared to others. Therefore, whenever a GEPTEP model is analysed, a strong emphasis must be made on how the market is represented, given that the resulting prices can highly affect investment decisions.

Hierarchical GEPTEP Models

In this sub-Section and the following Sections (0, 0, 0 and 0), we characterise co-planning equilibrium models. (next page) summarizes this information.

Bi-level models can represent the sequence between investment and operation decisions in either GEP or TEP problems separately. For instance, [38] considers a bi-level TEP by modelling market competition in the lower level and transmission expansion in the upper level. Some other authors develop a bi-level GEP by considering either perfect or imperfect competition in the lower level [68]–[71]. In order to properly classify and understand the existing hierarchical structure of GEPTEP problems, the difference between decisions and decision-makers must be pointed out.

Decision-makers can be typically classified as: GENCOs, TRANSCO(s), and Market Operator (MOR). On the other hand, decisions can be classified as: Generation Expansion Planning (GEP), Transmission Expansion Planning (TEP) and Market Operation (MO). Market Operation could also be split into Market Clearing (MC) and GENCOs Operation (GO). In reality, there is an inherent sequence in GEPTEP decision making: investment stage before market stage. Now, as we have pointed out previously in Table III, there even exist different sequential stages within the market stage. Conceptually, a complete GEPTEP model consists of multiple concatenated hierarchical stages; however, when decisions are assumed to be simultaneous, they are reduced mathematically to one single stage. In the remainder of this Section, and summarised in Table IV, we characterise GEPTEP co-planning models according to their conceptual sequence and their corresponding mathematical sequence.

In Table IV, we classify the GEPTEP models considering the investment and operation *decisions hierarchy*. To that purpose, Table IV, lists eight (I-VIII) different options, which are shown in the column space. The row space of Table IV represents the separate mathematical levels of each model. Please note that simultaneous decisions are represented in Table IV when decisions appear together in a single level. The simplest GEPTEP option, *option I,* is a single-level equilibrium model, which considers GEP, TEP and MO decisions simultaneously. Options II, III, and IV represent bi-level models, in which mathematically speaking there are only two levels.

Table IV: ***GEPTEP Model Classification Depending on Hierarchical Structure (mathematical levels 1-4 versus GEPTEP options I-VIII)***

	I	II	III	IV	V	VI	VII	VIII
1	GEP TEP MO	GEP	TEP	GEP TEP	GEP	GEP	TEP	TEP
2	/	TEP MO	GEP MO	MO	TEP	MO	GEP	GEP
3	/	/	/	/	MO	TEP	MO	MC
4	/	/	/	/	/	/	/	GO

[35]	/	[72]	[77]	[81]	[83]	[84][85]	[92]
[56]		[73]	[78]	[82]		[86][81]	
		[74]	[79]			[87][88]	
		[75]	[80]			[89][90]	
		[76]				[36][91]	

This means that conceptually speaking two of the three decision levels (GEP, TEP and MO) are considered to be taken simultaneously. Options V, VI and VII represent three-level co-planning models with the following structure: some investments are made in the upper level (GEP/TEP) given some other investments in the middle level (TEP/GEP), subject to market operation (MO) in the lower level. Finally, model VIII is a four-level model with the same structure as the previous three-level models; but also considers the market model is itself hierarchical. Additionally, some techniques can be applied to reduce the initial three-level model to a two-level structure as shown in [79] and [86].

Anyhow, reduction techniques are applied only for solving purposes, and therefore the underlying hierarchical structure remains an MLMF which is much more complex than an OLMF structure (when no anticipation of the market and only one leader is considered). This fact would imply to have, instead of a mathematical programme with equilibrium constraints (MPEC), an equilibrium programme with equilibrium constraints (EPEC), whose solution technique is more complex (see Section 0).

Equilibrium Structure Gaps

In terms of the commented structures of GEPTEP equilibrium models, we can identify some issues for potential further research. For instance, in Table III we have identified a potential model II that has not been proposed in the literature yet. This model could represent an electricity market with generation investment in the upper level and merchant transmission investments and operation in the lower level. Additionally, most of the research has focused on proactive models (see Table IV) type VII, but a large field of research on reactive models type V and VI still remains almost unexplored. Finally, the most realistic framework would be similar to structure VIII (four levels), where there is a sequence between TEP and GEP, while investments decisions anticipate market outcome and, at the same time, market clearing anticipates generation operation (as in hierarchical market models). However, this framework is intractable from an equilibrium point of view, and therefore iterative algorithms can help to simulate the real operation of the market.

Table V: Classification of GEPTEP Co-planning Models

AUTHORS	[86]/[36]	[72]/[73]	[35]	[78]	[77]/[79]	[92]	[88]/[90][12]/[87]	[84]	[89] /[91]	[81]	[82]	[74]/[75]	[80]$_1$, [94]$_2$, [93]$_1$, [40]$_2$
PUBLIC. YEAR	2006/2007	2013/2018	2009	2011/2012	2007/2012	2010	2013/14/17	2014	2014/2017	2017	2018	2015/2019	18/17/19/18
TYPE	OPTIMISTIC	OPTIMIST.	OPTIMISTIC	OPTIMIST.	OPTIMISTIC	OPTIMISTIC	OPTM./PESM.	OPTIMISTIC	PESSIMISTIC	PESSIMISTIC	OPTIMIS.	OPTIMIST.	ROBUST
NETWORK INVESTMENT	FIX INVESTMENT	BINARY NEW LINES	BINARY NEW LINES	BINARY NEW LINES	BINARY NEW LINES	BINARY NEW LINES	CONT /BINARY NEW LINES	BINARY NEW LINES	BINARY NEW LINES	BINARY EXP. /CONT.	BINARY UPGRADES	CONT./ BINARY N.L.	BINARY NEW LINES
TSO OBJECTIVE FUNCTION	Max Social Welfare	Max SW/ Max PR –IC (FB)	Max PR – IC With FB	Max Welfare-IC	Max Profits/ Min CP- IC	Several Planning Criteria	Min total Cost /MIN OC Min-Max	Min Weighted sum CC-GP	Min IC – SW	Min LIC +GIC+OC	Min IC +Exp.OC With FB	Min IC+OC	Min IC+OC
GENERATION INVESTMENT	CONT.	CONT.	CONT.	CONT.	BINARY NG	BINARY NG	CONT/ BINARY NG	BINARY NG	CONT	BINARY EXPANSION	CONT	CONT	CONT
GENCOs OBJECTIVE	Max Profit	Max Profit	Max PR-IC	Max Profit	Max PR & CapPay	Max PR-IC	Max Profit	Max Profit	Max Profit	Max Exp PR-IC	Max Exp PR-IC	Max Profit	—
ISO OBJECTIVE	Max Social Welfare /RD	Max Social Welfare	Min CP	Max SW	Min P. Mis. Min OC	Max SW	Min Cost Operation/	Min Accep. Bids	Max Social Welfare	MIN OC	Max Social Welfare	Max CR	Min OC
DYNAMICITY	STATIC	STATIC	STATIC	STATIC	STATIC	STATIC	STATIC	Muli-Period	STATIC	STATIC	STATIC	STATIC	STAT.$_1$/DYN$_2$
REGULATORY FRAMEWORK	PROACTIVE VS REACTIVE	PROACTIVE	OTHER[13]	OTHER	OTHER[14]	PROACTIVE	PROACTIVE	PROACTIVE	PROACTIVE	PROACTIVE - REACTIVE	REACTIVE	PROACTIVE	OTHER[15]
HIERARCHICAL STRUCTURE	MLMF	OLMF	ONE LEVEL	OLMF	MLOF/ MLMF	MLMF	MLMF	MLMF	MLMF	OLMF/MLOF	MLMF	OLMF	OLMF
OPERATION COMPETITION	STRATEGIC	PERFECT	STRATEGIC	STRATEGIC	STRATEGIC/ PERFECT	STRATEGIC	PERFECT	PERFECT	STRATEGIC	PERFECT	PERFECT	PERFECT/ STRATEGIC	PERFECT
UNCERTAINTY	NO	NO	**NO**	NO	YES	NO	NO/DEM/GEN	NO	NO	YES	NO	NO	YES
DEMAND ELASTICITY	ELASTIC	INELASTIC	INELASTIC	ELASTIC	ELASTIC/ INELASTIC	INELASTIC	INELASTIC	INELASTIC	ELASTIC	INELASTIC	INELASTIC	ELASTIC	INELASTIC
TIME REPRESENT.	1 HOUR	LOAD LEVEL	1 HOUR	1 HOUR	LOAD LEVEL	LOAD LEVEL	BLOCKS	1 HOUR	1 HOUR/ BLOCKS	BLOCKS	REPRESEN. PERIODS	1HOUR/ERP	REPRESEN. PERIODS
END EFFECT	Annual	Annual	Annual	Annual	NPV / Annual	NPV	Annual	NPV	Annual	Annual	Annual	Annual	Annual
STORAGE REPRESENT.	NO	NO / Short - Term	NO	NO	NO	NO	NO	NO	NO	NO	Short Term	Short/Short & Long-Term	NO
TEST CASES[16]	Chilean 32 /Cornell 30	IEEE-21 Garver-6	IEEE 14 bus	6-bus	6-bus/ IEEE-118	5- bus	4-Bus/Chilean 34/24 Node	Garver- 6	IEEE-118/ IEEE-14	IEEE-118	WEEC-240	4-bus	118/Chile 20/118/118
SOLUTION TECHNIQUE	LCP-SQP[17]	MIP	QCP[18]	MIP[19]	ITERATIVE[20] /MIP	Iterative Agent Based	MIP[21]/ CG[22]	Kth Best Algorithm	(DM-CP)[23]/ MILP	MBA[24] / MILP	MIP/ Iterativ. CG	MIP	Column Generation$_2$

[12] Subject to linear decrease in marginal costs.
[13] Simultaneous GEPTEP decisions
[14] GEPTEP in the upper level and Market Operation in the lower level
[15] GEPTEP in the upper level, uncertainty middle level, operation lower level
[16] When several cases are tested only the biggest one has been referenced.
[17] Sequential Quadratic Programing- Linear Complementarity Problem (1st level)
[18] Quadratically Constrained Program
[19] Authors compare NLP, MIQP and MIP approaches.
[20] Holistic Simulation by using Benders and the Lagrange Relaxation.
[21] Generation Strategies are enumerated and finally a MIP is solved.
[22] Column Generation and Disjunctive Cutting Plane.
[23] Hybrid algorithm using Diagonalization and Complementarity Reformulation.
[24] Moore Bard Algorithm.

Acronyms: SW= Social Welfare, CC = Costumer Cost, CP = Consumer Payment, IC = Investment Cost, OC= Operation Cost, ERP=Enhanced Representative Periods, CONT= Continuous, LIC= Line Investment Cost, GIC= Generation Investment Cost.

Regulatory Framework

From a regulatory point of view, GEPTEP co-planning models can be classified depending on the decision maker considered to be the leader (which implies which investment decisions are assumed to be taken first). Depending on whether GEP or TEP are considered to be first, the regulatory framework can be proactive or a reactive. Moreover, co-planning models can also be classified according to the level of competition in the market: markets with an oligopolistic structure versus those closer to perfect competition, both will be discussed below.

Proactive versus Reactive Planning Approaches

A key issue in generation and transmission expansion planning is the choice of which investment decision is considered to be taken first. Does the transmission planner take its decisions after the generation has been sited or do the generation companies plan their investments after transmission assets have been decided? What comes first, the chicken or the egg?

These choices are the proactive and reactive transmission planning approaches. Authors in [36] propose a proactive planning approach as a framework in which the network planner has the ability to influence generation investment and spot market behaviour. In terms of the hierarchy, it means that TRANSCO is the leader and the GENCOs that anticipate market outputs are the followers.Respectively, under a reactive planning approach, the network planner assumes that generation capacities are given, and then makes an optimization based only on the spot market equilibrium. Reactive planning is thus represented by a model with multi-leaders GENCOs and one or several TRANSCOs as followers. Authors in [36] consider an oligopoly structure and demonstrate theoretically how proactive planning leads to greater social welfare in comparison to reactive planning.

Some alternative approaches are available, like presented in [78] (please see Table IV). Here, a two-level model is defined, where the upper level represents the investment decisions (both GEP and TEP), while the lower level represents the market operation (MO). Authors in [78] additionally consider fuel supply as another investment variable.In practice, as mentioned in [25] most of the TRANSCO companies in the world follow a reactive approach, and, to the best of our knowledge, no institution has applied a strictly proactive approach as the one proposed in [36]. However, as mentioned in [87] there are some other approaches that are close to proactive planning. For example, the US government approved a regulation includes the concept of anticipative (proactive) transmission planning to obtain a higher social welfare [95]. In Chile, a regulation that enforces the consideration of coordination between transmission and generation has also been approved [96]. Additionally, in the current European context, ENTSOE plays the role of a centralised agent that proposes future planning pathways, coordinated regionally, and then generation companies can react to its decisions. Thus, under this regulatory context, a proactive planning approach would make more sense.

Proactive Planning Approach

Most of the literature in co-planning equilibrium models for GEPTEP have used a proactive planning approach. Proactive planning research can be summarised as follows. On one hand, authors in [86] extend the work done in [36]; they analyse different objective functions and consider a spot market where the distinctive ownership structures are reflected (one GENCO can own several units), as proposed in [66]. Authors in [88] extend the theoretical work done in [86] and [36] where the complete multi-level model was not solved and only a set of different fixed transmission investment plans were evaluated. The work done in [88] proposes the first complete model; however they relax the Cournot assumption and consider only perfect competition in the spot market. On the other hand, authors in [90] also define three levels and assume perfect competition in the market in the lower level, strategic generation expansion in the middle level and transmission expansion in the upper level. Compared to [88], [90] adds uncertainty in the demand and applies the model to a real-size case study. The same authors in [90] extend their work in [87] by proposing a pessimistic and optimistic network planner (the pessimistic case is used to eliminate multiple equilibria by considering the worst generation expansion case) to describe all possible outcomes of the EPEC in the lower level. The authors conclude that in practice, if multiple generation expansion exists in the equilibrium, proactive planning does not always yield the best welfare results, and it can even reduce social welfare.

Additionally, [89] extends this approach and proposes a model with Cournot strategic decisions in the market. Finally, [92] relaxes the Cournot assumption (in reaction to transmission prices) and proposes a two-level approach in the market outcome by considering an interaction between ISO market clearing problem and GENCOs optimal bidding strategies (please see 0 and Table IV), resulting in a four-level model. This model is solved by means of an agent-based methodology.

Apart from the three-level proactive approach, there are two-level approaches where transmission investment decisions are taken first and then generation investment and operation decisions are taken simultaneously. On the one hand, the work in [72] models the lower level based on the work of [58]. Authors in [72] consider perfect competition in the lower level and define different objective functions in the upper level, that are compared with a vertically integrated one-level approach. Additionally, they consider a network fee so the TRANSCO can recover investments in the case of a flow-based fee regulation, typically used in the US. Later, [73] extends the work in [72], choosing a pessimistic TRANSCO and demonstrating some subsequent uniqueness properties, battery expansion is also considered in their framework.

On the other hand, authors in [74] consider a stochastic bi-level model with merchant (for details on modelling of merchant TRANSCOs refer to [97] and [98]) investor of transmission in the upper level and wind expansion and market operation in the lower level, considering Cournot competition. Finally, authors in [75] and [76] apply the same structure, but consider storage expansion and Cournot competition in the lower levels. Additionally, [76] compares the bi-level model with the traditional an inelastic cost minimisation approach. Both works [74], [75] find counterintuitive results when considering Cournot competition in the lower level compared to a perfect competition case.

Reactive Planning Approach

As mentioned above, the reactive planning approach was first proposed in [86], where some theoretical properties were shown and some other practical results were presented for fixed transmission plans. Unfortunately, subsequent research is limited. In general, under this approach, several GENCOs are considered as the leaders, and a single TRANSCO as follower. However, it could also be the case that only one GENCO is the leader and the rest GENCOs and TRANSCO(s) are followers, this would represent an OLMF structure, which, as mentioned above, is simpler to solve.

There are only three subsequent studies on reactive planning. In [81], authors propose a new comparison between the proactive and the reactive approach. In contrast to the work done by [90], authors in [81] do not consider anticipation of market outcomes by GENCOs and propose the elimination of the multiple Nash equilibria by considering a pessimistic or optimistic TRANSCO. Additionally, authors in [82] propose a real size reactive planning approach in which merchant storage is decided in the Upper Level, while transmission investment and market operation are decided in the Middle and Lower Level respectively. Authors conclude that the co-planning of storage and transmission lead to greater cost savings than an independent storage planning. Authors in [83] propose a 4-level with merchant TRANSCOs.

Finally, in terms of transmission modelling, it is important to note that for all proactive planning models, capacity expansion of new lines is represented by binary variables, while, in reactive planning, line expansions are represented by continuous variables to keep the convexity of the lower level, as shown in [81]. However, in [82] transmission expansions are represented by binary variables by applying the dual formulation of the lower level and using the strong duality condition as it will be discussed in Section 0

Perfectly Competitive versus Oligopolistic GEPTEP Approaches

In the usual proactive planning approach, a centralised TEP and several GENCOs are considered. Thus, given the three-level structure of GEPTEP problems (see Section 0); there could be strategic decisions either on GENCOs operation decisions or on GENCOs investment decisions. As mentioned in 0, the competition between generators in the spot market, and their reaction to transmission prices, can be modelled as either Cournot, Bertrand or SFE. We will discuss the different approaches found in the literature for GEPTEP problems.

Competitive Market

Most of the GEPTEP hierarchical models consider perfect competition in the spot market (please see Table IV). This simplifies the solution techniques, and more importantly, guarantees that under certain conditions, uniqueness of the solution is achieved.
If perfect competition (both in GENCOs investment and market functioning) and cost minimisation objective are considered in both levels, there would not be a difference between a proactive bi-level decentralised GEPTEP problem and a centralised vertically integrated co-optimisation problem, as shown in [99]. In other words, if the objective function of both levels is aligned and a perfectly competitive market is considered, both approaches will render the same solution.

Oligopolistic Market

As mentioned above, there could be strategic behaviour either in the investment or in the generation operation decisions. If only strategic investment decisions are considered and no anticipation of the competitive spot market is assumed (simultaneous generation and perfectly competitive market operation), the problem will have an MPEC structure. However, even in this case, multiple Nash equilibria can arise. As mentioned in 0 no anticipation of the spot market is assumed in [72], [81] and [15]. In [73], [81] multiple equilibria are eliminated considering a pessimistic TRANSCO approach.
If only anticipation of the spot market is considered, there might still exist multiple Nash equilibria (as pointed out in [90]) given that an EPEC problem would be tackled. As mentioned in Section 0, in the context of proactive planning some models consider strategic decisions in both investment and operation levels, as shown in [89] and [92] (Cournot or SFE). However, they represent a MLMF structure, whose solution method does not guarantee a global optimum solution.

Regulatory Framework Gaps

In spite of the fact that proactive planning has been proven to lead to the most efficient investment and operation results (and most of the research has focused on its analysis), in practice, few jurisdictions have strictly applied this approach. Therefore, it is important to compare different regulatory contexts to be able to propose additional formulations of the GEPTEP problem for understanding the operation and investment strategies in an imperfect market structure. Additionally, the lower construction times for generation and the higher constructions times for transmission lines allow GENCOs to exercise strategic investment and operation decisions more easily. This scenario leaves an open field for future research on novel regulatory structures to model the entrance of new merchant GENCOs in the market.

Solution Techniques

In this Section, we present the techniques used to solve hierarchical GEPTEP co-planning problems. Depending on the *initial* hierarchical structure (please see Section 0), the techniques might be different. Therefore, in order to solve problems with a single leader, i.e., an OLOF or OLMF structure, the solution techniques for the arising Mathematical Programs with Equilibrium Constraints (MPECs) described in Section 0 are to be used. Alternatively, if there are multiple leaders in the upper level, i.e., an MLOF or MLMF structure, the techniques explained in 0 to solve Equilibrium Programs with Equilibrium Constraints (EPEC) are to be used.

Mathematical Programs with Equilibrium Constraints

When a bi-level problem is defined as an OLMF game (as defined in Section 0), its mathematical structure is seen as an MPEC or as a simple bi-level programming problem. As seen in Figure 2, the OLMF is a type of mathematical structure in which a single optimisation problem (Upper Level) is constrained by several simultaneous optimisation problems (Lower Level) that represent an equilibrium. In Figure 2, x and y represent lower and upper level decision variables respectively.
As explained in Section 0, in some cases, this lower-level equilibrium can be converted into a single optimisation problem. Nevertheless, even if this is possible, the resulting complete problem cannot be solved directly by classical optimisation techniques, because an optimisation problem is constrained by another optimisation problem.

$$Max\ F(x,y)$$

$$Subject\ to:$$

$$\begin{array}{cccc} Max\ f(x_1,y) & Max\ f(x_2,y) & \dots & Max\ f(x_n,y) \\ subject\ to & subject\ to & \dots & subject\ to \\ & & & \\ g_1(x_1,y) \le 0 & g_2(x_2,y) \le 0 & \dots & g_n(x_n,y) \le 0 \\ x_1,y \ge 0 & x_2,y \ge 0 & \dots & x_n,y \ge 0 \end{array}$$

Figure 2: ***Bi-level problem with an OLMF structure***

Therefore, in order to solve a bi-level problem with an OLMF structure, we can follow the next steps. First, the set of lower-level optimisation problems can be converted into a set of non-linear and non-convex constraints by applying the Karush-Kuhn-Tucker (KKT) (if the optimisation problem is convex) conditions. As seen in Figure 3, the resulting optimisation problem is constrained by the primal feasibility constraints, the dual feasibility constraints and the Complementarity Conditions (CC).

$$Max\ y\ F(x,y)$$
$$Subject\ to:$$

Dual
$$\partial L/\partial x_1 = 0 \quad \partial L/\partial x_2 = 0 \quad \dots \quad \partial L/\partial x_n = 0$$

CC
$$\lambda_1 g_1(x_1,y) = 0 \;\; \lambda_2 g_2(x_2,y) = 0 \dots \lambda_n g_n(x_2,y) = 0$$

Primal
$$g_1(x_1,y) \le 0 \quad g_2(x_2,y) \le 0 \;\dots\; g_n(x_n,y) \le 0$$
$$x_1, y \ge 0 \quad x_2, y \ge 0 \quad \dots \quad x_n, y \ge 0$$

Figure 3: ***OLMF problem with Lower Level KKT Conditions***

The resulting set of constraints is non-linear and non-convex, given the complementarity conditions of the problem. This lower level has the structure of a Mixed Complementarity Problem (MCP), and therefore the whole problem has the structure of an MPEC. Please note that bi-level (OLMF) problems are particular cases of MPECs. Now we list the most used techniques to solve this kind of problems. As mentioned in [100], these techniques can be divided into dedicated (efficient algorithms that ensure global optimality but require significant additional coding) and non-dedicated algorithms. We explain here the non-dedicated algorithms (that can be implemented directly using commercial software): NLP/ MPEC, Regularisation, Penalisation, MIP KKT-DUAL.

NLP/MPEC

The only non-convexity in Figure 3 is the one introduced by the complementarity conditions. Therefore, this problem can be solved directly using an ordinary NLP solver. However, given that this is a specific NLP structure embedded in an MPEC, specific solvers, such as PATH, that tackle directly this problem more efficiently can be used. Unfortunately, both nonlinear and MPEC solvers cannot guarantee a global optimal solution to the MPEC, given that all feasible points are non-regular [100], and consequently, solution methods can easily get stuck in a local optimum or not even find a feasible solution.

Regularisation

This method [100] relaxes the complementarity condition of the MPEC problem. Instead, the set of equations for $g_n(x_n, y) \leq t$ are solved. Then the NLP problem for small values of t is iteratively solved. The solution of each iteration will be the initial point of the following iteration; this process is faster but only provides a local optimum point solution for the MPEC.

Penalisation

The penalisation approach [100] is similar to the regularisation. Conversely, in this case, the complementarity conditions are penalised in the objective function by a parameter that is reduced along the iterations until a sufficiently small value of the parameter is reached. As before, the solution of each iteration will be the initial point of the following iteration.

MIP KKT- DUAL

As an alternative, the non-linear problem described in Figure 3 can be converted into a MILP (when the upper level objective function is linear) by linearizing the complementarity conditions. This linearisation can be achieved by applying the methodology proposed by Fortuny-Amat in [101] or by the discretisation method proposed in [102]. In the first case, a disjunctive formulation is applied to transform complementarity constraints into binary constraints. This is done by splitting the original constraint into two disjunctive constraints limited by a large enough parameter. This is usually known as the Big M constraints.

This method is, by far, the most used method to solve bi-level problems. However, most of the papers that use it do not explicitly mention a method to determine the Big-M values. In fact, as mentioned in [103] if these values are small, suboptimal solutions can appear, and conversely, too large Big-Ms can lead to numerical issues (when different variable magnitudes are reflected in dual variables), such as unstable solutions or large execution times. In [100], a method is proposed to define Big M values by mixing the regularisation and KKT-MIP previously commented methods. Authors show that this method is more efficient computationally speaking and it reaches the optimal solution in more cases compared to other methods. This method is proposed for linear bi-level problems; but it seems to be also efficient for convex problems in general.

Additionally, instead of applying the whole set of KKT conditions, the complementarity conditions can be replaced by the strong-duality conditions (where the objective function of the dual problem equals the objective function of the primal problem), which together with its primal and dual feasibility conditions, leads to an equivalent primal-dual formulation. In [104] a comparison of the KKT and the primal-dual formulation is presented and applied to a vulnerability analysis of the power system. The authors find that the primal-dual approach is more efficient because the size of the problem is highly reduced. This is the result of the lower number of Big Ms (alternatively index constraints or SOS1 variables can be used to programme disjunctive constraints[105].) needed to linearise the strong duality conditions compared to those needed to linearise the complementarity conditions (it depends on the ratio #variables / #constraints).

Equilibrium Problem with Equilibrium Constraints

In case of structures with multiple leaders and one follower or multiple followers, it will be more difficult to solve the resulting problem, given that the resulting formulation consists of several optimisation problems (equilibrium) subject to several optimisation problems (equilibrium). This problem can be seen as a collection of several MPECs. As shown in [60], in order to solve this problem, the following techniques are available: a) *Diagonalisation algorithms,* the MPEC of every agent is solved sequentially one after the other. b) *Simultaneous solution method*, all problems are solved simultaneously by defining the strong stationary condition c) *System of inequalities with equilibrium constraints*, used when the problem has finite strategies.

Unfortunately, the solution of multilevel equilibrium problems can only be guaranteed for the case of OLMF models (MPECs). For MLOF and MLMF (EPECs) problems, there is no guarantee of the existence of the equilibrium. As mentioned in [60], there is still a lack of understanding of the existence of EPECs solutions, thus, only simulation models and approximation algorithms are applied. Additionally, we can have hybrid methods as the *one level reformulation of bi-level games*. In this case, the lower level is reformulated by its equivalent KKT conditions and then it is inserted into every optimisation problem in the upper level. Then the KKT conditions of the whole problem are formulated and solved again. However, the resulting solution might not be an optimum. Ex-post validation should be carried out to verify its optimality. An example of this approach can be found in [91].

Albeit the difficulty of solving these mathematical structures, in the literature there are several models that tackle more than two levels, by trying to reduce the multi-level problems into a two or one level equivalent problem. For instance, authors in [92] propose a coordination framework to take into account the reaction from GENCOs by adopting generation expansion decisions within a four level problem. They solve the coordination problem iteratively using agent-based modelling and a search-based optimisation technique. In [106] they further extend the model and develop an iterative process by simulating the interaction between TRANSCOs and the ISO and they propose a multi leader – multi follower agent based model. They consider both several TRANSCOs and GENCOs. Additionally, we can find an EPEC problem when only one TRANSCO is considered in the upper level and multiple investing GENCOs in the middle level to anticipate the market outcome of the lower level. In this case the middle and lower level result in a MLMF structure and thus an EPEC formulation is solved as presented in [90].

Finally, it is important to note that, in most co-planning models, generation expansion is modelled as a continuous variable, as shown in [25], [85], [35] and [88]. This assumption responds to the need to obtain convexity conditions in the lower levels, and implies that (in most cases) only repowering of existing units is represented.
Alternatively, other authors represent the expansion decisions with integer variables, as [13], [79] and [84], but in these cases only the GEP model is solved for new wind generators. Finally, to the best of our knowledge, only [81] and [87] consider binary variables in both investment levels of the GEPTEP problem, which yields non-convex sub problems that can only be solved by using complex algorithms such as Column generation (CG) or the Moore Bard Algorithm. Authors in [87] propose a CG and cutting plane algorithm to solve a three-level proactive problem. The CB algorithm is close to the usual diagonalisation technique, but it considers a master problem that creates a meaningful solution to the sub problem that is solved by a diagonalisation-like procedure. This algorithm guarantees a global solution and efficient computation times.

Solution Technique Gaps

In the case of MPEC problems, there is still an active field of research for finding efficient methods to solve these optimisation problems. As mentioned before in [103], Big M is the most common technique to solve the one-level reformulation of bi-level programs. However, small values of Big Ms can lead to suboptimal solutions and large constants can lead to numerical issues (if different orders of magnitude are present in the dual variables of the lower level). Additionally, some authors have tackled the consideration of binary variables in the lower level but all the solutions imply the implementation of complex dedicated algorithms [81], [82], [87]. Finally, even though some progress has been done in the resolution of EPECs [87] there is even more space for research in this area, given that its application to real size cases is still an immature area of knowledge.

Most recent developments

In this Section, we introduce the most recent research on co-planning equilibrium models. This research focuses on modelling the detailed operation of storage technologies and on representing renewable uncertainty using novel hierarchical structures.

Representation of Storage in GEPTEP Co-planning Models

Only [81] is the only study that considers long-term hydro storage in equilibrium models, but a simplified version that does not consider reservoir management. To the authors' knowledge, two reviewed papers have addressed short-term storage modelling in GEPTEP co-planning models.
On the one hand, authors in [73] consider storage expansion and perfect competition in the spot market simultaneously formulated in the lower level. Authors in [73] show that adequate storage investment can reduce line investment cost of the TSO. They also show that investment in a zonal market can be suboptimal compared to a nodal market.
On the other hand, in [82] investment in merchant storage resources is considered in the upper level. The authors use a representative period approach to simulate the time steps in which the period of study is divided. Authors demonstrate that merchant storage is economically feasible under the case study considered.
More recently, authors in [75] propose a co-planning model that includes Cournot competition in the market and the representation of short-term (batteries) and long-term (hydro) storage resources with a representative-period formulation that includes a transition matrix and cluster indices as proposed in [45]. Additionally, authors in [75] find counterintuitive results when a proactive approach is considered with Cournot competition in the market.

Representation of Uncertainty in Investment and Operating Decisions

Given the complexity of GEPTEP hierarchical models, most of the papers reviewed do not consider the modelling of uncertainty (as seen in) in their formulations. Accordingly, given that the correct implementation of renewables depends mainly on the introduction of the uncertain availability of the resources, renewables[25] are usually not included in detail in these models.
As mentioned in Section 0, probabilistic and stochastic approaches were the most common way to represent uncertainty For instance, [79] considers a stochastic approach with scenarios for wind levels and demand. However, it considers traditional load blocks and therefore it is not suitable for adequately simulating storage operation. Authors in [79] study how different wind subsidies schemes affect the total welfare of the system. They conclude that transmission investments highly conditions the investment in wind. They consider different hydro seasons, limiting the maximum energy produced at each season, and consider a Weibull distribution to introduce stochasticity in wind speed that limits the maximum generation capacity of each wind unit. They also consider a load block approach. Recent developments in uncertainty representations have introduced other techniques such as robust optimisation, mainly

[25] Additionally, determining support schemes is an important field of research that has not been assessed by GEPTEP models but has been assessed separately in bi-level GEP and network constrained GEP [125], [126].

by the application of Adaptive Robust Optimisation (ARO), which has proved to be computational efficient and to represent properly the long-term uncertainties [40].

In this sense the most recent work on robust GEPTEP considers a Min-Max-Min approach in which simultaneous GEP and TEP decision are taken in the upper level, uncertainty realisation in the middle level and operation in the lower level [40], [93]. In particular [80] considers stochastic programming and robust optimisation to deal with both long- and short-term uncertainties. Finally, some other authors additionally consider a certain type of reliability criteria [94] and [107]. Please note that the computation efficiency of the algorithms used to solve robust problems have permitted to consider multistage dynamic planning approaches, which had been previously of limited application [40], [93].

A different approach for representing uncertainty is presented in [87]. Authors introduce uncertainty in generation investment, by using similar techniques to those used in robust optimisation. Therefore, authors in [87] take into account the possible multiple generation investment equilibria resulting from a hierarchical model (see Section 21). Therefore, instead of considering the parameters as the uncertainty set, the authors consider the multiple investment equilibria (resulting from the middle level) as their uncertainty set.

It is important to highlight the recent prolific research in robust optimisation. The theoretical background to solve robust optimisation problems is close to the dual theory and the techniques used to solve hierarchical models. However, in hierarchical models, the *levels* considered represent either different agents or decisions. Conversely, in robust optimisation, the *levels* considered typically represent different instances of uncertainty realisation. For instance, in [80], both the GEP and TEP expansion decisions are made in the second level where the worst operational case is simulated and in the third level corrective measures are taken to minimise operational costs. This robust optimisation framework can be an important field of research that, together with stochastic programming, is able to couple long and short-term uncertainties in capacity expansion planning

Gaps in Storage and Uncertainty Modelling Approaches

Renewable uncertainty and storage operation are still wide fields of research in co-planning equilibrium models. Given the properties of equilibrium models, there is an interesting field of research to study and compare extreme competition cases, where the uncertainty can come not only from the fuel and sources availability but also on the multiple equilibria that can arise from imperfect competition. Additionally, detailed time representation and novel solution techniques can permit us to model more complex markets.

Concluding remarks

In this paper we addressed the GEPTEP problem. First we considered the GEPTEP co-optimisation problem in a *centralised environment* in which a vertically integrated utility takes investment and operation decisions. Then, we focused on the GEPTEP co-planning problem in *market environment*, where strategic behaviour and sequential decisions of decentralised agents was studied.

The main findings of this literature review are twofold:

i) Given the usual tractability trade-off in planning problems it is difficult to determine the best modelling options to represent GEPTEP problems, however we found that: a) in general, considering lumpy transmission investments might be more important than representing a detailed network. b) in contrast, given that the economies of scale in generation investment are much lower than in transmission investment, lumpy generation investment can be sometimes disregarded. c) Finally, as shown by [108], a thorough uncertainty representation can be more important than representing generation operating constraints in a detailed manner.

ii) For the case of GEPTEP co-planning problems in a market environment, we found that it is a very useful framework to model more realistic market structures. In general, the most studied proactive approach, which renders a higher welfare, is still not spread around countries. We found, that even if there is perfect competition in the operation, considering the strategic sequential investment decisions between transmission and generation can highly change the planning results. Additionally, the consideration of merchant investors helps to give insights on how to define optimal support schemes. Finally, some counterintuitive results arise when considering imperfect competition in the market operation, i.e., under Cournot competition, allowing trade between areas (by building more lines) can decrease total welfare [74], [75], [86].

We found the following gaps in the literature:

i) Modelling Approaches: There is an active field of research on spatial and temporal resolution, resource adequacy and economics of energy production. ii) Equilibrium structure: Most of the equilibrium structures studied, consider a two, three or even four level traditional proactive approach, however, some proactive structures and most reactive structures remain unexplored. iii) Regulatory Structure: In spite of the fact that proactive planning has been proven to lead to the most efficient investment and operation results, in practice, few jurisdictions have strictly applied this approach. Therefore, it is important to compare different regulatory contexts in order to understand optimal operation and investment strategies in imperfect markets. iv) Solution Technique: In the case of MPEC problems, there is still an active field of research for finding efficient and standard methods to solve these equilibrium problems. Additionally, even though some progress has been achieved in the resolution of EPECs, there is even more space for research in this area, given that its application to real-size cases is still an immature area of knowledge. v) Most recent developments: Renewable uncertainty and storage operation are still wide fields of research in co-planning equilibrium models. On the one hand, more studies on the complementarity between transmission and storage investment are necessary, as well as the joint consideration of both short term and long term storage. On the other hand, given the properties of equilibrium models, there is an interesting field of research to study and compare extreme competition cases, where the uncertainty can come not only from the fuel prices and the availability of generating units, but also from the multiple equilibria that can arise from imperfect competition. Finally, given that perfect information is a strong assumption, including imperfect information theory in the GEPTEP problems can make these models more useful for real applications.

3 Transmission- and generation-expansion planning under perfect competition

This task develops a mathematical model to capture the transmission-expansion planning currently in use by TSOs. Such models work under the assumption of a perfectly competitive market and, hence, resolve to a cost-minimisation approach. We will build such a model as a benchmark for comparison with the equilibrium model in this task. By undertaking this task in close collaboration with our partner TSO, we acquire invaluable technical information on how decisions are currently being taken and what are the main decision-analytic features to take into account in transmission-expansion models.

3.1 Deterministic Transmission and Generation Expansion Planning

In this report, we develop the mathematical formulation of the co-optimization problem between of the Generation Expansion Planning and Transmission Expansion Planning (GEPTEP), each of which has been widely addressed (in a separated way) in the literature. Hence, in this report we are going to formulate a cost minimization deterministic GEPTEP, which is meant to serve as a benchmark for a future bi-level GEPTEP model. The motivation for the development of a bi-level model is to have a tool that allows us to understand more deeply the strategic interactions between agents in the liberalized market.

In terms of co-optimization problems, in [3] we find a wide literature review on GEPTEP models. It includes a large classification which goes from a time resolution to network representation classification. At a first stage, we are going to include the main operations constraints which might be relaxed or simplified according with size or time resolution representation.

Notation

This Section contains the main notation used in the models presented in this document.

Sets

$y \in Y$	year
$p \in P$	periods
$rp \in RP$	representative periods
$\Gamma_{rp,p}$	set of correspondence between rp and p
p	final period
$d \in D$	nodes
$g \in G$	generator unit g
$t(g) \in T$	thermal units
$h(g) \in H$	storage units
$hf(h) \in HF$	short-term storage units
$hs(h) \in HS$	long-term storage units
$GAD(g,d)$	set of all possible *g* located at node *d*
$GED(g,d)$	set of existing g located at node *d*
$GCD(g,d)$	set of candidate g located at node *d*
$LA(d,d')$	set of all possible lines from node *d* to *d'*
$LE(d,d')$	set of existing lines from node *d* to *d'*
$LC(d,d')$	set of candidate lines from node *d* to *d'*
Hpp'	Univocal correspondence between period *p* and *p'* $\in \Gamma_{rp,p}$

Parameters

$pMaxProd_g$	Maximum capacity of technology g	MW
$pMinProd_g$	Minimum capacity of technology g	MW
$pMaxFlow_{dd'}$	Maximum flow in line *dd'*	MW
$pReactance_{dd'}$	Reactance of line *dd'*	[p.u]
$pFCost_t$	Fuel cost of technology t	€/MWh
$pFixCost_t$	Fix operation cost of thermal generator t	€
$pInvC_g$	Annualized investment cost g	€
$pSUpCost_t$	Startup cost of thermal generator t	€
$pInvC_{dd'}$	Annualized investment cost of line *dd'*	€
$pDemand_{ypd}$	Demand Intercept at year *y* period p at node d	MW
$pDSlope$	Demand Slope	€/MW

$pEfficiency_h$	Efficiency of storage unit *h*	[p.u]
$pProdFct_h$	Production Function of *h*	[p.u]
$pInflow_{ph}$	Energy inflows for period *p* storage *h*	MWh
$pMaxLevel_h$ $pMinLevel_h$	Max/Min reservoir level of storage unit *h*	MW
$pMaxCons_h$	Maximum consumption of storage unit h	MW
M	Time window	h
$pERt_t$	CO2 emission rate of technology t	CO2/MWh
pW_{rp}	Weight of each representative day	[p.u]
pSB	Base Power	MW
$NRP_{rp,rp'}$	Number of periods from rp to rp'	[p.u]
EFOR	Expected Forced Outrage	[p.u]
$pVOLE$	Value of lost energy	€/ MW

Variables

$vProd_{ypgd}$	Production at year y period p of generator g at node *d*	MW
$vNewGen_{ygd}$	Investment status at year y of generation unit g at node d	{0,1}
$vNewLine_{ydd'}$	Investment status at year y of line connecting node d to d'	{0,1}
$vFlows_{ypdd'}$	Flows at year y at period p from node *d* to *d'*	MW
vUC_{yptd}	Commitment status of unit *t* in node *d* at period *p*	{0,1}
$\mathrm{vStartUp}_{yptd}$	Start status at year *y* period *p* of the thermal generator *t* at node *d*	{0,1}/MW
$vTheta_{ypd}$	Voltage angle at year y period p node *d*	p.u.
$vDemand_{ypd}$	Demand at year y period p at node d	MW
$vLevel_{yphd}$	Level at year y period p of storage unit h at node d	MW
$vCon_{yphd}$	Consumption at year y period p of storage unit h at node d	MW
$vSpill_{yphd}$	Spillage at year y period p of storage unit h at node d	MW

Model Description

In general, in most of real-size models, intertemporal restrictions such as ramping or spinning reserves are excluded from the model, and a detailed hydro system is usually neglected. Thus, we formulate a model with the same characteristics based mainly on the Star Net model, adding generation expansion constraints and including some additional simplifications.

Additionally, given that there exists a tradeoff between representing in detail the operation of the system and executing a long-term model with a representative amount of years, we use a representative's day framework. It has been established in [45] the importance of a correct representation of short-term operation for long-term decisions. In particular, authors in [45] show that this is especially true for storage technologies which can operate both in short (batteries) and long (hydro) term. Thus, authors in [45] present a thoughtful comparison of the available time representation modeling frameworks and apply them to a storage investment model. As a result, [45] proposes a representative-period model with transition matrix and cluster indices. This framework is an extension of the usual representative days, by considering transitions between representative periods to be able to model inter-period constraints rather than only intra-period constraints. In this report, we will follow this approach to represent time, slow and fast storage constraints.

Finally, three different types of models are formulated to give account of the tradeoff between a detailed representation in operation and a relaxed considerations of such constraints. Accordingly, the increase in the size of the models depend mainly on the inclusion of integer variables. In this GEPTEP model there are four set of integer variables that might increase the complexity of the problem: investment decision in lines and generators, unit commitment variables and start-up of thermal generators.

As mentioned before, this model is meant to serve as a benchmark for a bi-level model in which usually TEP represents the upper level. This condition allows us to have discrete transmission investment decisions and, as a consequence, we will consider them binary in our three models. On the other hand, we can remove or relax the discrete decisions related to generation expansion and operation. Therefore, we define 3 distinctive models: 1) Complete: this model considers all possible binary decisions in the model, investment, unit commitment and star-up. 2) Relaxed Model: this model keeps the unit commitment and generation investment decisions but the variables are considered continuous instead of binary. 3) Simplified Model: in this case we exclude unit commitment operation decisions and we relax investment decisions.

Table 6: Models Description

	Simplified	Complete	Relaxed
Type of problem	MIP	MIP	MIP
Objective Function	Equation (2)	Equation (1)	Relaxed O.F
Operation	(3)-(5), (13)- (16)	(3), (6) - (16)	(3),(6)- (16)
Unit Commitment Start-Up Shut-Down	Not Included	Binary Decisions	Continuous Decisions
Generation Investment	Binary Decisions	Binary Decisions	Continuous Decisions
Network Investment	Binary Decisions	Binary Decisions	Binary Decisions

Objective Function

Our Objective Function (O.F) is a cost minimization function which includes investments costs, fixed and variable operation costs and CO_2 emission costs. For each year, we have a discount factor that allows us to compare financial flows at the base year. Additionally to cost minimization problems we can find reliability considerations. For instance [14] proposes an iterative algorithm to solve the GEPTEP taking into account the network reliability at each of the iterations. Nevertheless, we can introduce global reliability measures as the Energy Non- Served (ENS).

An additional concern is how to treat the end effect of the optimization, this refers to how to consider the last period of the optimization and the terminal conditions of the temporal constraints. For instance, we can solve this issue by including recovery values for the assets as shown in [38]. With this procedure, we can internalize additional information in the model to make more accurate decisions for investment times and to remove distortion of endless operating investments. On the other hand, we can run an extended simulation or have a fixed finishing criterion. For instance [25] uses 40 year horizon, which means replicating 20 years and taking only the result of first 20 operating years. For the moment we apply a fixed finishing criterion.

From now on, we will define some of the equations including Unit Commitment Constraints (UCC) and some other excluding them. From now on index p refers hours belonging to the representative days $Pa = \{p | p \in \Gamma_{rp,p}\}$

Objective Funtion including UCC

$$\begin{aligned} TotalCost = & \sum_{ygd} (Y - y + 1) * pInvC_g * (vNewGen_{ygd} - vNewGen_{y-1,gd}) \\ & + \sum_{ydd'} (Y - y + 1) * pInvC_{dd'} * (vNewLine_{ydd'} - vNewLine_{y-1,dd'}) \\ & + \sum_{y,(p,rp)\in\Gamma_{rp,p},t,d} pW_{rp} * pFCost_t * vProd_{yptd} \\ & + \sum_{y,(p,rp)\in\Gamma_{rp,p},t,d} pW_{rp} * pFixCost_t * vUC_{yptd} * D_y \\ & + \sum_{y,(p,rp)\in\Gamma_{rp,p},t,d} pW_{rp} * pSUpCost_t * vStartUp_{yptd} * D_y \\ & + \sum_{y,(p,rp)\in\Gamma_{rp,p},t,d} pERt_t * vProd_{yptd} * pW_{rp} * pCO2price * D_y \\ & + \left(\sum_{y,(p,rp)\in\Gamma_{rp,p},g,d} vENS_{ypd} * pW_{rp} * D_y \right) * pVOLE \end{aligned} \quad (1)$$

O.F excluding UCC

$$
\begin{aligned}
Min\,TotalCost = \;& Min\,TotalCost \\
= & \sum_{y,(g,d)\in GCD} (Y-y+1) * pInvC_g \; * \left(vNewGen_{ygd} - \; vNewGen_{y-1,gd} \right) \\
& + \sum_{y(d,d')\in LC} (Y-y+1) * pInvC_{dd'} * \left(vNewLine_{ydd'} - vNewLine_{y-1,dd'} \right) \\
& + \sum_{y,(p,rp)\in \Gamma_{rp,p},t,d} pERt_t * vProd_{yptd} * pW_{rp} * pCO2price * D_y \\
& + \left(\sum_{y,(p,rp)\in \Gamma_{rp,p},t,d} vENS_{ypd} * pW_{rp} * D_y \right) * pVOLE
\end{aligned} \quad (2)
$$

Where D is the discount rate

$$
D_y = \frac{1}{(1-d)^y}
$$

For the case with UCC we consider a unique type of plant with fixed production capacity per type of generator. However, we can add a binary variable to specify different capacity levels per technology as described in [79].

Constraints

We now describe the set of constraints to be included in the GEPTEP formulation, as in the O.F case we will have two alternative formulations depending on whether the constraint is affected by the unit commitment or not.

Power Balancing Constraint

We consider the power balance at each node of the system.

$$
\sum_{g\epsilon GAD} vProd_{ypgd} + vENS_{ypd} + \sum_{d'\epsilon LA} vFlows_{ypdd'} - \sum_{d'\epsilon LA} vFlows_{ypd'd} + \sum_{d'\epsilon LA} \frac{vCon_{yphd}}{pEfficiency_{h\epsilon GAD}} = pDemand_{ypd} \quad (3)
$$

Capacity Constraint

In the initial prototype we model the unavailability of the units as a fixed historical proportion of the total capacity (EFOR). In some cases, the nonscheduled maintenances can be simulated in order to introduce some uncertainty in the model. For instance [22] uses a Monte Carlo approach to model the generation outages and [14] uses a minimum load curtailment algorithm together with ELOL and LOLP measures.

Excluding UCC

Existing units

$$0 \leq vProd_{ypgd} \leq pMaxProd_{g} * EFOR \quad \forall g \in GED, \forall ypd \tag{4}$$

New Units

$$0 \leq \; vProd_{ypgd} \leq pMaxProd_{g} * vNewGen_{ygd} * EFOR \quad \forall g \in GCD, \forall ypd \tag{5}$$

Including UCC

Existing Units

$$vProd_{ypgd} \leq pMaxProd_{g} * vUC_{yptd} * EFOR \;\; \forall g \in GED, \forall ypd \tag{6}$$

$$\left(pMinProd_{t} * vUC_{yptd}\right) * EFOR \;\; \leq vProd_{tybsd} \; \forall g \in GED, \forall ypd \tag{7}$$

New Units

$$vProd_{ypgd} \leq [pMaxProd_{t} * (vUC_{yptd} + \left(1 - vNewGen_{ytd}\right)_{t \in ged})] * \; EFOR \;\; \forall g \in GCD, \forall ypd \tag{8}$$

$$vProd_{ypgd} \leq \left(pMaxProd_{g}\left(vNewGen_{ygd}\right)\right) * EFOR \; \forall g \in GCD, \forall ypd \tag{9}$$

$$\left(pMinProd_{t} * vUC_{tybs} - \left(1 - vNewGen_{ty}\right)\right) * EFOR \;\; \leq vProd_{tybs} \; \forall g \in GCD, \forall ypd \tag{10}$$

The representation of generation expansion is a key feature that differentiates the various GEPTEP approaches. In some cases, mainly when an equilibrium model is tackled, the generation expansion is modeled as a continuous variable, as shown in [25],[85],[35] and [88]. This consideration responds to the need of convexity conditions in the lower levels for multi-level approaches, and additionally implies that we only represent repowering of existing units. On the other hand, some others authors represent the decisions with integer variables, as [13], [79] and [84] in which only expansion in wind generation is included.

With the previous remarks we propose two ways of representing generation expansion for new units.

a) Excluding UCC. In equation (5) we can limit the power capacity of a new generator depending on whether it is installed or not.

b) Including UCC: In equations (8) , (9) and (10) we limit power capacity considering the commitment of the units. These equations are the result of the linearization of the product between the commitment and investments status variables. We use the big M approach to attain such a result. In the case of the minimum production (10) we need only one constraint in contrast to maximum capacity where we need both (8) , (9).

Commitment, startup logic of thermal units

$$vUC_{typ} - vUC_{typ-1} < vSU_{typ} \ \forall t \ \in GAD, \quad \forall yp \tag{11}$$

$$vUC_{ytp'} = vUC_{ytp(p,rp)} \ \forall t \ \in GAD, \forall y, \forall (p,rp), rp' | \ NRP_{rp,rp'} > 0 \tag{12}$$

Where $p' = pf(p', rp') + NP_{rp-1,t}$ *and pf is the last hour of rp*

The unit commitment constraint (11) tell us that if a unit is not committed in time t and then it is committed in time t+1, then the unit has to be started. Additionally, equation (12) is the condition to represent the connection between representative days, it states that the last hour of a representative period has to be equal to the first hour of the following representative period.

Storage Constraints

Equations (13) and (14) represent the storage balance conditions as proposed in [109]. Equation (13) represents short-term storage i.e. batteries, when only intraday operation is considered. Equation (14) is considered jointly with equation (13) when long-term storage i.e. hydro is modeled. Therefore, for long-term storage, reservoir management is followed up across the entire year, as opposed to the rest of constraints in which only intraday operations are included. While the detailed formulation and explanation of this representation of storage is presented in [23], we briefly explain it here for clarity.

The reservoir energy balance is verified for a given time window. For instance, if a 168h window is chosen, the reservoir balance equation (14) will be verified at the end of every week. This balance the sum of production, consumption and spillage from the reservoir during the whole week. Note that not all 8760 hours are solved; only a number of hours belonging to a set of representative days are chosen. Please note that in equation (14), $\Gamma_{rp,p}$ indicates which hours of the year correspond to the chosen representative days, while $H(p', p)$ maps each hour of the year to its corresponding hour in the appropriate representative day.

In hydro storage we will have two types of units, regular units in which inflows to the reservoir are only parameters ($pInflow$) and pumping units in which we have both parameters and decision variables inputs such as consumption($vCon$) .

$$vLevel_{yph_fd} = vLevel_{y,p-1,h,d} + vLevel_{y=1,p=1,h,d} + pInflow_{yph_fd} - vSpill_{yph_fd} - \frac{vProd_{yp''h_fd}}{pProdfct_{h_f}} + \frac{vCon_{yph_fd}}{pProdfct_{h_f}} \quad \forall h_f \in GED, p < pf, \ \forall yphd, \tag{13}$$

$$vLevel_{yphd} = vLevel_{y,p-M,h,d} + vLevel_{y=0,p=1,h,d} + \sum_{p'}^{p} \sum_{p''} \left(pInflow_{yphd} - vSpill_{yphd} - \frac{vProd_{yp''hd}}{pProdfct_h} + \frac{vCon_{yphd}}{pProdfct_h} \right) : \psi'_{yphd} \quad \forall h \in GED, p < pf, \ \forall yd, \tag{14}$$

$$with\ p` = p - M + 1\ and\ p\ \in Ps, \qquad p'' \in H(p', p'')Ps = \left\{ ps | \frac{ps}{M} \in Z^+ \right\}$$

We will not consider a detailed hydrological topology. However, this can be easily generalized in a straightforward way. Finally, to differentiate between hydro reservoirs and batteries we set $vInflow$ values to 0 in the case of batteries. The variable $vProd$ refers to discharges in batteries and energy production in hydro units, as well as $vCon$ means pumping consumption in hydro units and charging decisions in batteries. In equations (15) and (16) we set the boundaries on the storage level and consumption, which might represent volume of reservoir or capacity of batteries.

$$MinLevel_h \leq vLevel \quad \leq MaxLevel_h \ \ \forall h \in GED, \forall ypd \tag{15}$$

$$0 \leq \frac{vCon_{yphd}}{pEfficiency_h} \leq pMaxCons_h \qquad \forall h \in GED, \forall ypd \tag{16}$$

Network Modeling

Hereafter we describe the two main types of network modeling used in the literature. They choice of the alternative depends on a tradeoff between a detailed representation of the network and the computational tractability. We finally chose to model our network with a DC approach.

Transportation Model

In the case of the transportation model (also known as transshipment or pipeline), the network is seen as a pipeline in which flows can be decided regardless voltage limitations. In several long-term commercial models the network is represented in this way. Some of these are: Markal [5], ReEds [9], LIMES [15] or SWICTH [12]. These models consider continuous investment variables to in order to reach the representation of bigger systems. This approach allows them to remain within linear programming, at the expense of a simplified network representation. On the other hand, [25] uses discrete line investment decisions together with the transshipment model. This choice is supported by [25] in two ways a) they conclude that a transshipment model with binary decisions approximates well to a DC power flow model with binary investment decisions. b) For the specific US case consider in [25], a zonal model is studied in which voltage laws can be depreciated as a consequence of recurrent local loops in the network .

As a consequence, for the case of existing lines we will have the following formulation:

$$pMaxFlows_{dd'} \geq vFlows_{ypdd'} \geq -pMaxFlows_{dd'} \qquad \forall (d,d') \in LE, \forall yp \tag{17}$$

On the other hand, for the case of candidates lines we have the following formulation:

$$vFlows_{ypdd'} \geq -pMaxFlows_{dd'} * vNewLine_{ydd'} \qquad \forall (d,d') \in LC, \forall yp \tag{18}$$

$$-vFlows_{ypdd'} \geq -(\ pMaxFlows_{dd'} * vNewLine_{ydd'}\ ) \qquad \forall (d,d') \in LC, \forall yp \tag{19}$$

DC linearized Model

In the DC linearized model, we add to the transportation model the limitation on voltages.

For existing lines:

$$vFlows_{ypdd'} = pSB * \frac{vTheta_{ypd} - vThetha_{ypd'}}{pReactance_{dd'}} \qquad \forall (d,d') \in LE, \forall yp \tag{20}$$

For candidate lines:

Regarding the expansion of the network we might find two distinctive approaches. We can include expansion only for new lines or repowering of existing lines by the addition of circuits into an interface. After applying the Big M approach, as in the case of generation expansion planning, we get as a result, equations

(21) and

(22) in which $pMaxFlow$ is the upper bound for the capacity of the transmission lines. In other words, $pMaxFlow$ is used as the value for Big M.

$$-vFlows_{ypdd'} \geq \left(-pSB * \frac{vTheta_{ypd} - vThetha_{ypd'}}{pReactance_{dd'}} - pMaxFlows_{dd'}(1 - vNewLine_{ydd'})\right) \forall(d,d') \in LC, \forall yp \quad (21)$$

$$vFlows_{ypdd'} \geq \left(pSB * \frac{vTheta_{ypd} - vThetha_{ypd'}}{pReactance_{dd'}} - pMaxFlows_{dd'}(1 - vNewLine_{ydd'})\right) \forall(d,d') \in LC, \forall yp \quad (22)$$

Reference angle

In order to solve the previous equations we need to have a reference angle.

$$vTheta_{ypd*} = 0 \quad (23)$$

Integer constraint

$$vNewLine_{y-1,dd'} \leq vNewLine_{ydd'} \; \forall(d,d') \in LC \; \forall y \quad (24)$$

$$-vNewGen_{y-1,gd} + vNewGen_{ygd} \geq 0 \quad \forall ygd \quad (25)$$

Constraint (24) and (25) tells us that once a line or generator is invested it will be operational in the rest of the planning horizon. As mentioned before, this constraint can be stricter if we chose to include a recovery value from assets. However, constraint (24) and (25) would hold if we finally simulate a planning horizon longer than investments life time.

As for the case of generation expansion, in transmission expansion we can model the investments decision either as integer variables like the approach followed by [14] , [25], [13] or binary decisions as done in [22], [84],[85],[35] and TEPES model. The decision on the utilization of binary variables instead of integer decreases the search space and computation time.

Case Study

Data

Figure 4 shows the system considered in the case study. The system consists of 9 lines, all with a total transmission capacity of 800 MW. There is demand in all nodes and existing generation in nodes 1-4 and 6 (see Table VII). There are three candidate lines and two candidate generators (represented with dotted lines), their characteristics can be seen in *Table VIII* and Table IX respectively. Additionally, for this study case, 4 representative days (24 hours each) are chosen, a window of 168 h is selected and the model is run for a 1-year horizon.

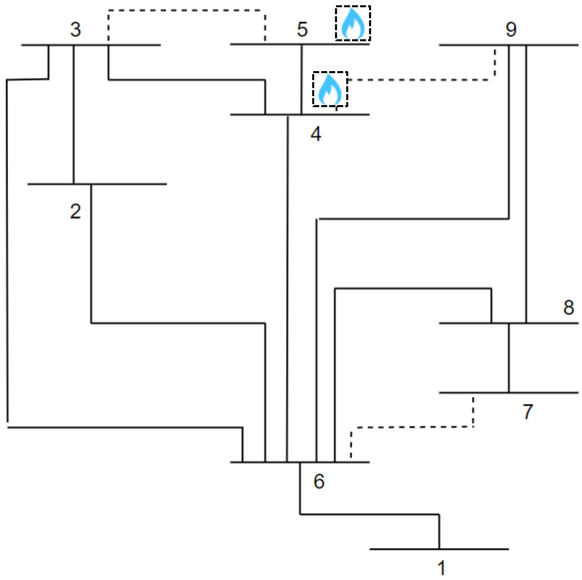


Figure 4: Network

Table VII: Existing Generation

Node	Technology	Max Capacity (MW)	Fuel Cost (€/MWh)
1	Nuclear	771.6	15
1	CCGT4	667.1	24
1	ImportedCoal_Bituminous	194.4	44
1	FuelOilGas	441.8	120
2	DomesticCoal_Anthracite	588	48
2	OCGT1	400	67.5
2	CCGT1	500	42
3	BrownLignite	203	50.92
3	CCGT2	500	45
3	OCGT2	400	70.5
4	ImportedCoal_SubBituminous	150.4	49.14
4	CCGT_3	500	48
4	OCGT_3	400	73.5

6	Hydro	200	0

Table VIII: Candidate Lines

From Node	To Node	Reactance [p.u]	Total Investment Cost (M€)	Capacity (MW)
4	9	0.07	7.5	800
3	5	0.03	7.5	800
6	7	0.06	7.5	800

Table IX: Candidate Generators

(G, TEC)	Node	Annual Inv Cost [k€/MW]	Fuel Cost (€/MWh)	Capacity (MW)
(C2,CCGT)	6	29	24	667
(C3,OCGT)	5	32.5	73.5	400

Results

Table X shows the resulting capacity expansion in transmission lines for each one of the models. As we can see, the transmission expansion is the same for all models, this suggests that, depending on the network configuration, the transmission decisions might not change when unit commitment decisions are relaxed or neglected.

Table X: Transmission Expansion

	Lines Invested	Capacity (MW)	Annual Inv Cost (M€)
COMPLETE	(9-4) (6-7)	1600	15
RELAXED	(9-4) (6-7)	1600	15
SIMPLE	(9-4) (6-7)	1600	15

However, every model tested results in different generation investment. This is true mainly because generation decisions are continuous for the Relaxed and Simple model. As seen in Table XI, in the Complete model the binary decision is taken and all available capacity for CCGT and OCGT is invested. On the contrary, on the Relaxed case only a 46% of available capacity is invested of the OCGT and in the Simple case no investment is decided for the OCGT generator. We can naturally explain this because the more flexibility of the system implies that minimum production constraints are no considered and therefore the resources can be used to its total capacity.

Table XI: Generation Expansion

	Generation	Generation Exp (MW)	Annual Inv Cost (M€)
COMPLETE	(C2,CCGT), (C3,OCGT)	667+400	40
RELAXED	(C2,CCGT), (C3,OCGT)	667+230	20+9.2
SIMPLE	(C2,CCGT)	667	40

Additionally, we analyze the results in operation of the system.

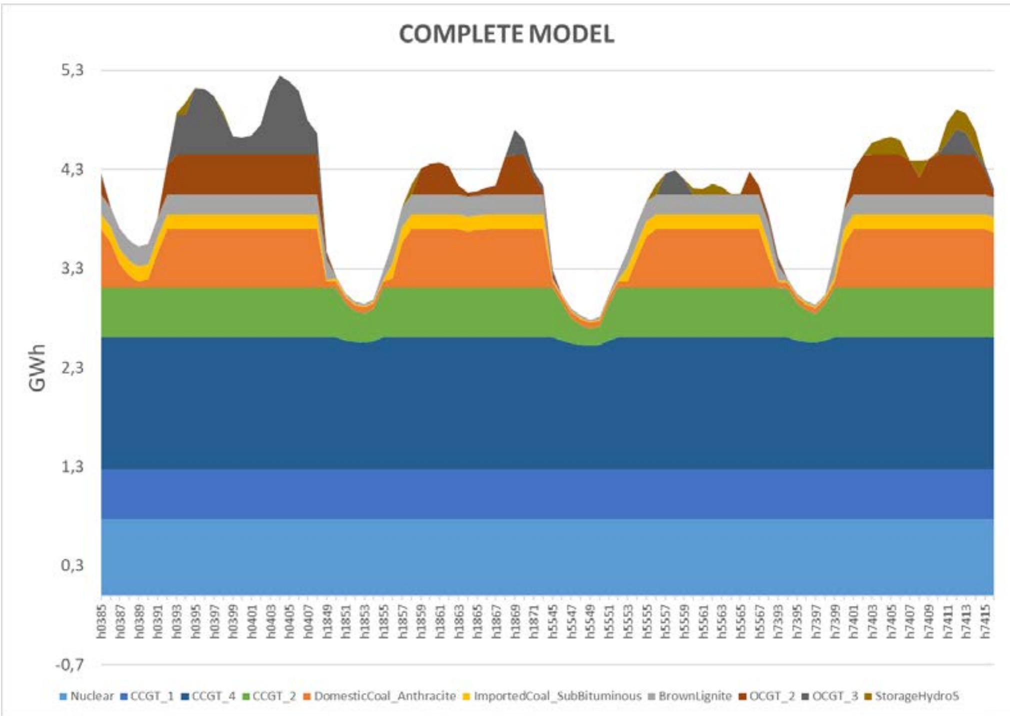
Figure 5 shows the dispatch of the system per generator for each one of the models for the chosen representative days. As we can see, the merit order remains the same per technology and generator in all the models. However, we can see the implications of considering binary commitment and start-up variables. For instance, in the complete case, OCGT_2 is used for long periods in order to avoid shut-downs and therefore the start-up costs, this implies using less hydro (as seen in *Figure 6*) and increasing the total operation cost.

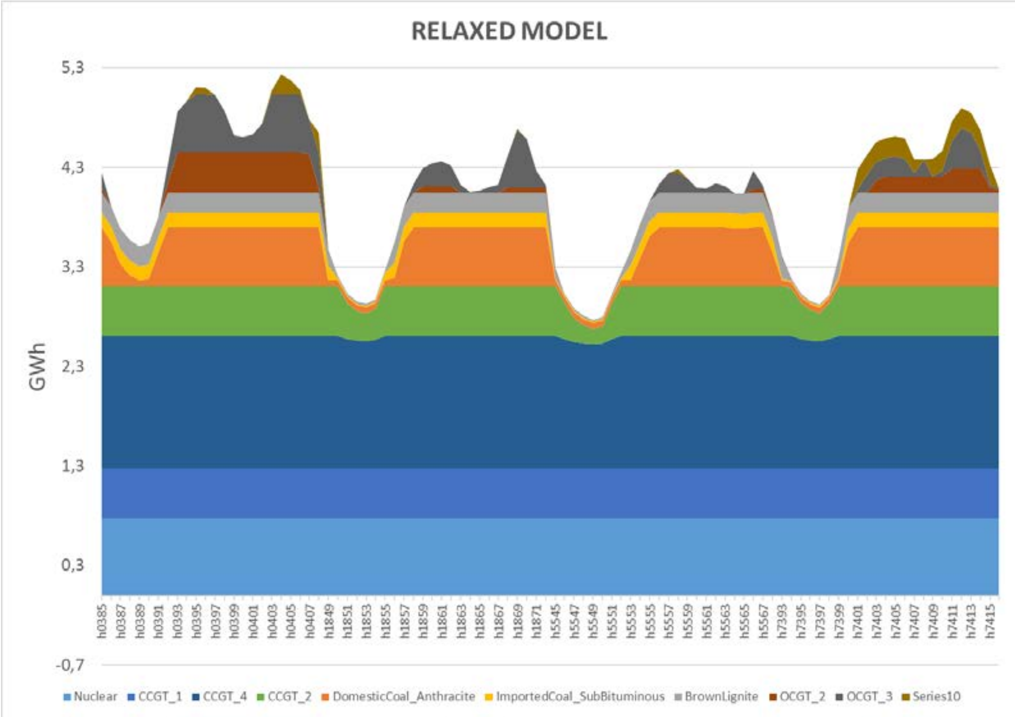
In the Relaxed Model, given that commitment and start-up are now continuous, we see that the previous effect is now smoother. Additionally, hydro production can be used more flexible and it replaces the two highest picks of demand. This implies less utilization of OCGT_2. Finally, in the Simple Case, we can see that the generators do not stop, given that star-up costs and minimum production constraints are neglected. Moreover, in this case, it is decided to invest in less generation because, given the current flexibility, it is cheaper to use the most expensive fuel generator instead of investing in new generation. Therefore total cost decreases.

Table XII: Total Costs

	Fuel Costs (M€)	Start-up and Commitment cost (M€)	Total Operation and Investment Costs (M€)
COMPLETE	954	306	1315
RELAXED	946	294	1284
SIMPLE	941	0	976

Figure 5: Dispatch





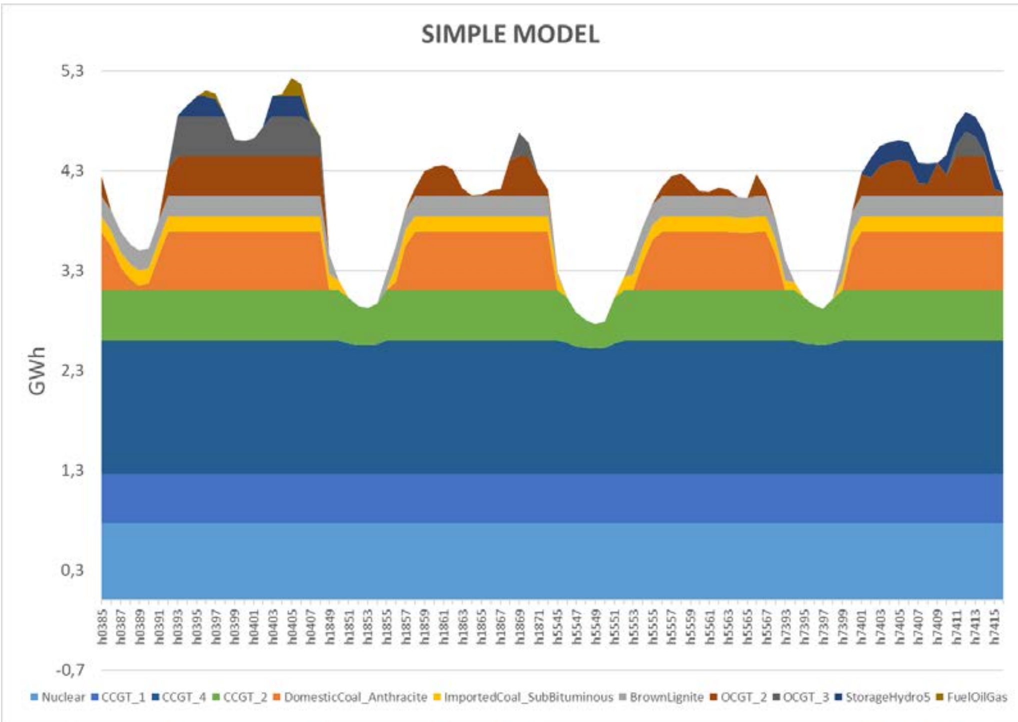
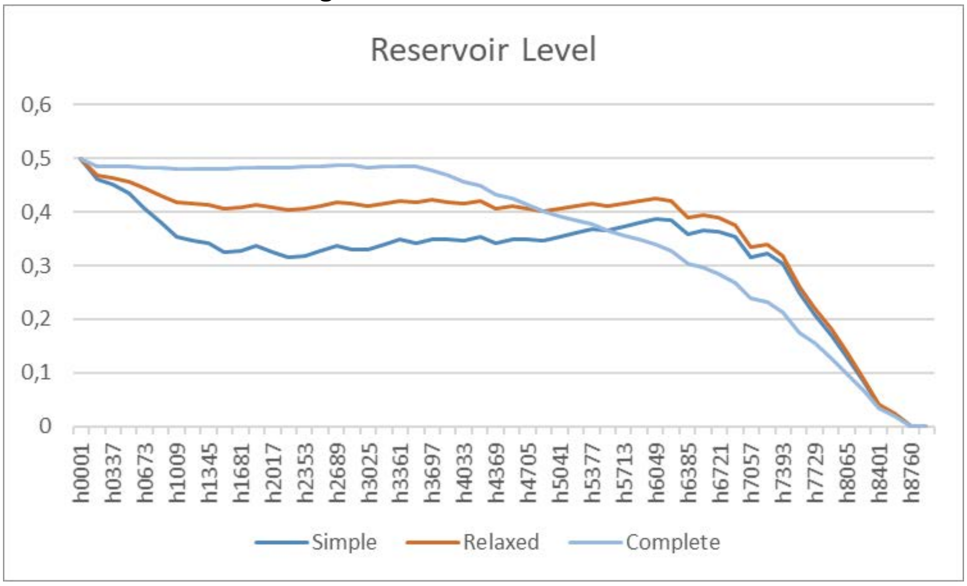


Figure 6 shows the evolution of the reservoir for each one of the models. As we can see, for the Complete Model the evolution of the reservoir is less flexible and the total energy kept is higher than in the other cases. In other words, given the startup condition of thermal units and the lower flexibility of the system, only 2.31 GWh of water are used during the year (which is a peaking unit in this case). As a consequence, the relaxed

model is an intermediate case, where total hydro energy used is 3.53 GWh. Finally, the Simple Model is the most flexible one where the most hydro energy is used (4.1 GWh) and more variability in seen the in evolution of the reservoir.

Figure 6: Reservoir Evolution



Finally in Table XIII we can see the size and CPU of each model. The model is coded in GAMS, solved with GUROBI and run on a computer with 3.4 GHz processor and 32 GB of RAM. As Table XIII shows, the size of the complete and relaxed model in terms of number of variable is the same. However, the number of discrete variables in the complete case represents a 33% of the total variables and increases exponentially the CPU time for solving the problem. However, despite the differences in solving time and complexity the results between the complete and the relaxed models defer only in the magnitudes of the cost but the investment and operation decisions are essentially the same. Thus, this suggests that small inaccuracy of having a relaxed model is compensated by the high reduction in computational time. On the other hand, the size of the Simple Model is reduced compared to the Complete and Relaxed model, however the computational time difference is so small that the inaccuracies introduced by the simple model might not compensate such a small time reduction.

Table XIII: Size and CPU time

	Number of variables	Number of discrete variables	CPU time (s)
COMPLETE	6980	2359	9200
RELAXED	6980	4	1

SIMPLE	4628	4	0.5

Conclusions

In this Section we formulate a co-optimization problem and we show a small study case to analyze the results of the proposed model. We formulate a compact model that tries to represent operation in the most detailed way handling the size of the problem with a time representation reduction. Additionally, we propose three different model in which we relaxed some of the discrete decision in order to simplify the problem. Finally we find that a the Relaxed Model, which includes continuous unit commitment conditions is the one that meets better the accuracy of operation at the least computational expense.

3.2 Comparing Scenario-Based Transmission and Generation Expansion Planning Models Under Uncertain Wind Production

The grid-scale deployment of renewables, spurred by the adoption of ambitious renewable portfolio standards by many governments, has prompted research into new and innovative grid expansion planning methods. The main difficulties facing grid-scale renewable deployment stem from the complication of short-term grid operations due to the variability and intermittency inherent to wind and solar production, as well as long-term uncertainties in demand growth, economic and regulatory conditions, weather conditions, and grid disruptions due to natural disasters, all of which complicate the evaluation of long-term grid expansion strategies. Scenario-based TEP/GEP models, which optimize grid expansion decisions with respect to multiple future operational scenarios, are known to be robust to short- and long-term uncertainties in power system conditions, and therefore hold promise as planning tools in the era of renewable integration.

Scenario-based planning methods are typically applied to two-stage or multi-stage planning problems, in which the planner must make one set of immediate, first-stage decisions under uncertainty, and another set of second-stage decisions in the future when the uncertainty has been realized (Maloney and McCalley, 2017); (Birge and Louveaux, 2011). The second-stage decision variables are often constrained by or coupled to the values of the first-stage decision variables, and one set of second-stage variables is defined for each scenario considered by the model. In scenario-based TEP/GEP models, first-stage decision variables represent investment in new generation or transmission infrastructure, and second-stage variables represent operational variables such as generation production levels and transmission network flows. The operational variables are obviously constrained by investment in new power system infrastructure.

Scenario-based planning techniques represent uncertainties as sets of potential operational scenarios (i.e. sets of possible system parameters), and make planning decisions based on the outcome of the decision in each of these scenarios. In this way, scenario-based planning solutions achieve robustness to uncertain power system conditions. Despite their apparent advantage over conventional/deterministic planning methods, little is known about the trade-offs and similarities between the various scenario-based planning methods that are commonly studied or used in practice. Therefore, the aim of this study was to compare four scenario-based TEP/GEP models in a large variety of power system conditions in order to identify general (i.e. non-case specific) similarities and differences between the various model formulations.

The four scenario-based planning models we examined are: stochastic programming, minimum-maximum cost robust programming, minimum-maximum regret robust programming, and mean-value programming. We review the mathematical formulation of each model in Section 2.2. These scenario-based planning techniques are among the most widely used and studied in the grid planning literature, and each has a range of interesting applications. Stochastic programming is perhaps the most widely studied technique, which assigns probabilities to the scenarios and minimizes the expected cost of the planning solution. Mean-value programming is closely related to stochastic programming and can be viewed as its naïve counterpart, in which uncertain grid parameters are fixed to their mean values in a deterministic TEP/GEP model. The minimum-maximum cost/regret models are examples of "robust optimization" techniques, in which the maximum cost or regret (defined in Section 2.2.4) of the planning solution in any scenario is minimized. Robust techniques do not require probability information about the scenarios, which can be especially advantageous when the scenarios represent specific events such as grid contingencies (i.e. grid component failures), power plant retirements, or policy changes, whose probabilities are difficult or impossible to estimate.

We did not consider planning methods such as Monte-Carlo simulation because these methods do not produce definitive planning solutions. Monte Carlo-like methods effectively map a set of operational scenarios to a set of planning solutions by solving the deterministic TEP/GEP model for each scenario. A definitive planning solution may be extracted from this set of planning solutions via a decision rule, but the optimal planning solution is not immediately apparent. The methods that we examined, on the other hand, solve only one optimization problem and produce definitive TEP/GEP solutions.

We discuss the formulation of our TEP/GEP models and modeling assumptions in Sections 0 , 0, and 0 as well as the selection of the wind capacity factor scenarios in

Section 0. The results are presented in Section 0. We also discuss the conclusions and possible avenues for future research 0.

Formulation

In this Section we present the formulation and methods to study the scenario based transmission and generation expansio planning. In Section 0 we introduce the notation to be used in the formulation. In Section 0 we present the benchmark model and in Section 0 we present the scenario based models to be compared.

Notation

Sets/Indices

$s \in S$	Operational scenarios for hourly level of available wind energy over one year
$p \in P$	Periods
$rp \in RP$	Representative days
$\Gamma_{rp,p}$	Mapping from active periods in *P* to *RP*
$g \in G$	Generators
$t \in T \subset G$	Thermal generators
$w \in W \subset G$	Wind generators
$d \in D$	Set of nodes
$GAD(g,d) \subseteq GXD$	Set of all ordered pairs of generators and nodes in the system (generator *g* is located at node *d*)
$GED(g,d) \subseteq GXD$	Set of ordered pairs of existing generators and nodes in the network
$GCD(g,d) \subseteq GXD$	Set of ordered pairs of candidate generators and nodes in the network
$LA(d,d') \subseteq DXD$	Set of all ordered pairs of nodes denoting transmission lines in in the network (transmission line from node *d* and *d'*)
$LE(d,d') \subseteq DXD$	Set of ordered pairs of nodes denoting existing transmission lines in in the net-work
$LC(d,d') \subseteq DXD$	Set of all ordered pairs of nodes denoting candidate transmission lines in in the network

Parameters

$pMaxProd_g$	Maximum power production of generator *g*	MW
$pMaxFlow_{d,d'}$	Maximum power flow along transmission line from node *d* to *d'*	MW

$pWind_{p,s}$	Normalized (p.u.) level of available wind power at period *p* for scenario *s*	MW
$pReactance_{d,d'}$	Reactance of transmission line from *d* to *d'*	[p.u]
$pFuelCost_t$	Fuel cost of thermal generator *t*	€/MWh
$pInvCost_g$	Annualized investment cost in generator *g*	€/MW
$pInvCost_{d,d'}$	Annualized investment cost in transmission line from *d* to *d'*	€
$pDemand_{p,d}$	Power demand at period *p* at node *d*	MW
$pWeight_{rp}$	Weight of representative period *rp*	[p.u]
$pENSCost$	Energy non served cost	€

Variables

$vNewGen_{g,d}$	Investment decision in new generator *g* at node *d*	{0,1}/MW
$vNewLine_{d,d'}$	Investment decision in new transmission line from node d to	{0,1}/MW
$vProd_{p,g,d,s}$	Production at period *p* of generator *g* at node *d* and scenario *s*	MW
$vPNS_{p,d,s}$	Power non served at period *p*, node *d*, and scenario *s*	MW
$vFlow_{p,d,d',s}$	Flow at period *p* from node *d* to *d'* in scenario *s*	MW
$vTheta_{p,d,s}$	Voltage angle at period *p* of node d in scenario *s*	[p.u]
ζ	auxiliary variable	€

Basic TEP/GEP Model Formulation and Modeling Assumptions

In this paper, we optimize transmission and generation expansion in a simulated power grid comprising five nodes with electricity demand and a mix of existing wind and thermal generators and transmission lines, four candidate generators, and 14 candidate transmission lines over a one-year planning horizon. The models take the perspective of a central planner and consider 10 operational scenarios for the hourly level of available wind power in the system over one year. Our aim was to observe systematic differences between the models in terms of their TEP/GEP solutions and associated fixed and variable costs.

The basic TEP/GEP model we use was adapted from (Gonzalez-Romero et al., 2019). The model was adapted from GAMS to Pyomo for convenience. The mathematical formulations of the four scenario-based TEP/GEP models that we examined only differ in the form of their objective functions (and, for the case of mean-value programming, in the number of operational scenarios considered by the model). Therefore, we begin this Section by reviewing the basic TEP/GEP model features that are common to all four of the scenario-based models we studied before discussing differences between them later on.

Our basic TEP/GEP model takes the perspective of a central planner with a one year planning horizon. Investments in additional generation or transmission made at the beginning of the year are immediately available for production or transmission, so we assume that construction time for all facilities is zero. The decision variables in the basic TEP/GEP model include the first-stage variables representing investment in new generation and transmission infrastructure: $vNewGen_{y,g,d}$ and $vNewLine_{y,d,d'}$, as well as second-stage variables representing generation production levels, transmission network flows, node voltage angles, and a Power-Not-Served (PNS) slack variable: $vProd_{p,g,d,s}, vFlow_{p,d,d',s}, vTheta_{p,d,s}, vPNS_{p,d,s}$. Notice that the second-stage variables are indexed by the operational scenario, s, but the first-stage variables are not. However, the basic TEP/GEP model is deterministic, so only one operational scenario is considered ($|S| = 1$).

Let $DV = \{vNewGen_{g,d}, vNewLine_{d,d'}, vProd_{p,g,d,s}, vFlow_{p,d,d',s}, vTheta_{p,d,s}, vPNS_{p,d,s}\}$ be the set of all decision variables. We refer the reader to the list of symbols for definitions of the other symbols and model parameters used in the formulation.

In general, each scenario-based planning method minimizes the total system cost, which is the sum of transmission/generation investment costs and the cost of operating the system to meet demand:

$$\min_{DV} \sum_{(g,d)\in GCD} pInvCost_g * vNewGen_{g,d} + \sum_{(d,d')\in LC} pInvCost_{d,d'} * vNewLine_{d,d'} + \sum_{(p,rp)\in\Gamma_{rp,p},g,d,s} pWeight_{rp} * [pFuelCost_t * vProd_{p,g,d,s} + pENSCost * vPNS_{p,d,s}] \tag{26}$$

We assume that wind generators have zero fuel cost and we do not penalize wind curtailment. Given that we consider hourly periods, the energy of each hour coincides with the power, and therefore we compute the total Energy Non Serve Cost as pENScost*vPNS. Let us also point out here that we have used a representative days formulation to reduce the number of operational variables in our models. Therefore, the variable costs computed by our models are only approximations of the true full-year variable costs associated with each TEP/GEP solution.

The second-stage operational variables are only defined over four representative days or 96 hours of the year instead of the full 8760 hours. We clustered 365 24-hour demand profiles into four clusters via k-means clustering, and selected the demand profiles with least Euclidean distance to the cluster centers as the four representative days. The representative day demand profiles therefore capture the variance between clusters of demand profiles throughout the year but are still "prototypical" of the days within their respective clusters. The variable costs of these four representative days, when weighted by the number of days in their respective clusters $pWeight_{rp}$ as in the third summation term of equation (105), should approximate the full-year operational costs, and therefore the planning results should approximate those of a more detailed full-year planning model [reference: Diego's paper on representative day formulations]. The 96 periods corresponding to the hours of the representative days are called "active periods", and the mapping $\Gamma_{rp,p}$ maps active periods to their corresponding representative days. The notation $(p, rp) \in \Gamma_{rp,p}$ denotes a valid active period-representative day pair.

The only operational constraint in our model is the node balance constraint,

$$\sum_{(g,d)\in GAD} vProd_{p,g,d,s} + \sum_{(d,d')\in LA} vFlow_{p,d,d',s} - \sum_{(d',d)\in LA} vFlow_{p,d',d,s} + vPNS_{p,d,s} = pDemand_{p,d} \forall d \in D, p \in P, s \in S \quad (27)$$

which ensures that the demand for power is satisfied at every node and at every period. The PNS slack variable is heavily penalized in the objective function ($pENSCost$ = 10,000 M-Euros/MWh) to discourage load-shedding. However, the penalty is reduced later to a more reasonable value when we compute the out-of-sample variable costs for the TEP/GEP solutions produced by our models.

The rest of the constraints in our model are physical, and include generation capacity constraints for existing and new generators,

$$0 \le vProd_{p,g,d,s} \le pMaxProd_g \forall (g,d) \in GED, p \in P, s \in S \quad (28)$$

$$0 \le vProd_{p,g,d,s} \le pMaxProd_g * vNewGen_{g,d} \forall (g,d) \in GCD, p \in P, s \in S \quad (29)$$

generation capacity constraints for existing and new *wind* generators,

$$0 \le vProd_{p,w,d,s} \le pMaxProd_w * pWind_{p,s} \forall (w,d) \in GED, p \in P, s \in S \quad (30)$$

$$0 \le vProd_{p,w,d,s} \le pMaxProd_w * pWind_{p,s} * vNewGen_{w,d} \forall (w,d) \in GCD, p \in P, s \in S \quad (31)$$

transmission capacity constraints for existing and new transmission lines,

$$-pMaxFlow_{d,d'} \le vFlow_{p,d,d',s} \le pMaxFlow_{d,d'} \forall (d,d') \in LE, p \in P, s \in S \quad (32)$$

$$vFlow_{p,d,d',s} \le pMaxFlow_{d,d'} * vNewLine_{d,d'} \forall (d,d') \in LC, p \in P, s \in S \quad (33)$$

$$vFlow_{p,d,d',s} \ge -pMaxFlow_{d,d'} * vNewLine_{d,d'} \forall (d,d') \in LC, p \in P, s \in S \quad (34)$$

DC power flow approximation voltage angle constraints for new and existing transmission lines,

$$vFlow_{p,d,d',s} = pS_{Base} * \frac{vTheta_{p,d,s} - vTheta_{p,d',s}}{pReactance_{d,d'}} \forall(d,d') \in LE, p \in P, s \in S \quad (35)$$

$$vFlow_{p,d,d',s} \leq pS_{Base} * \frac{vTheta_{p,d,s} - vTheta_{p,d',s}}{pReactance_{d,d'}} \quad (36)$$

$$+pMaxFlow_{d,d'}(1 - vNewLine_{d,d'})\forall(d,d') \in LC, p \in P, s \in S$$

$$vFlow_{p,d,d',s} \geq pS_{Base} * \frac{vTheta_{p,d,s} - vTheta_{p,d',s}}{pReactance_{d,d'}} \quad (37)$$

$$-pMaxFlow_{d,d'}(1 - vNewLine_{d,d'})\forall(d,d') \in LC, p \in P, s \in S$$

and non-negativity and integrality constraints for $vNewGen_{g,d}$ and $vNewLine_{d,d'}$.

$$vNewGen_{g,d} \geq 0 \forall(g,d) \in GCD \quad (38)$$

$$vNewLine_{d,d'} \in \{0,1\} \forall(d,d') \in LC \quad (39)$$

Therefore, our basic TEP/GEP model is thre following:

$$\min_{DV}(105)$$

subject to (27) - (39)

The demand at each node is perfectly correlated in our model –that is, we assume that the hourly demand profile at each node is a scalar multiple of the same basic hourly demand profile. This assumption, though not entirely realistic, is reasonable in small grids in which drivers of demand such as temperature and time of day are strongly correlated across nodes. Similarly, the hourly capacity factor of wind generation is the same at every node (the wind capacity factor scenarios apply uniformly to all locations). This is also a reasonable assumption in small grids, since wind availability is strongly correlated over small geographical areas.

Other notable aspects of our model include its lack of ramping restrictions and unit commitment constraints for thermal generators (e.g. minimum run times, start-up and shutdown costs and times, etc.). As a result, all of our models likely over-invest in wind generation since the thermal generation can instantaneously respond to changes in the level of net demand [ref: Graduate thesis sent by Sonja]. The model also takes a brownfield planning perspective–that is, we assume that there are existing wind and thermal generators and transmission lines in the system at the start of the planning period. We took this approach in order to study the application of these planning methods in settings in which the existing generation/transmission infrastructure is unlikely to signficantly change–e.g. for projects with relatively short planning horizons and fast construction times. We therefore decided to study the models under a variety of power system conditions, including differing levels of existing wind penetration and demand at the nodes.

In general, our approach was to observe and compare the TEP/GEP solutions of the four scenario-based planning models in three different cases of existing wind penetration (in which wind generators respectively accounted for 0%, 13%, and 39% of existing generation capacity) and 12 different demand level cases at each node for a total of 36 grid cases/system conditions. We then estimated the out-of-sample variable costs for each of the 144 TEP/GEP solutions by computing the variable costs of the basic TEP/GEP model in which the first-stage decision variable values had been fixed to those found in the TEP/GEP solution and the scenario s was an out-of-sample wind capacity factor scenario. We computed 10 out-of-sample variable costs for each of the 144 TEP/GEP solutions and took the mean of these 10 costs as the "estimated" variable costs associated with the TEP/GEP solution.

The purpose of testing the models under such a wide variety of power system conditions was to avoid drawing conclusions about the models that were case specific. We hoped to draw general conclusions about the differences and similarities between the four scenario-based planning models and the trends we observed in their TEP/GEP solutions.

Scenario-Based TEP/GEP Model Formulations

In this Section, we present the mathematical formulations of the four scenario-based TEP/GEP models. As we mentioned, the four models only differ in the form of their objective functions due to their different treatments of the operational scenario costs.

Stochastic Programming

Perhaps the most widely studied scenario-based planning technique is stochastic programming, in which operational scenarios are assigned probabilities and the expected cost of the TEP/GEP solution is minimized. The most natural application setting for stochastic programming occurs when the operational scenarios represent samples of a random system parameter such as the hourly level of demand or, as in this paper, the hourly capacity factor of wind generators in the system, since these scenario data can be sampled or estimated directly from wind speed data. In this case, the objective of the model is to minimize the “sample average” of the scenario costs, so it is natural to assign probabilities of 1/10 to the 10 scenarios considered by the model, as we have done. The application of stochastic programming becomes less straightforward when the future scenarios represent specific future events (e.g. the retirement of a specific coal plant in the year 2030), to which probabilities are difficult to assign and which are less easily thought of as samples of a random variable since they are usually binary outcomes and only occur once.

Let P_s be the known or estimated probability of scenario $s \in S$. The stochastic programming TEP/GEP model is

$$\min_{DV} \sum_{(g,d)\in GCD} pInvCost_g * vNewGen_{g,d} + \sum_{(d,d')\in LC} pInvCost_{d,d'} * vNewLine_{d,d'} + \sum_{(p,rp)\in\Gamma_{rp,p},g,d,s} P_s * pWeight_{rp} * [pFuelCost_t * vProd_{p,g,d,s} + pENSCost * vPNS_{p,d,s}] \quad (40)$$

subject to constraints (27)-(39).

Mean-Value Programming

The naïve counterpart to stochastic programming is sometimes called mean-value programming, in which random or uncertain system parameters are fixed to their sample average value. In other words, instead of considering multiple scenarios for hourly capacity factor of wind generation in the system, the model considers a single scenario in which the hourly capacity factor of wind is equal to the sample average of the 10 scenarios. This technique is even less straightforward and perhaps impossible to apply when the scenarios represent specific events whose probabilities are difficult to estimate, and whose expected values are difficult to interpret.

In this scenario-based planning technique, the set of operational scenarios S is reduced to only one operational scenario s'. Specifically, we let the hourly capacity factor of wind generation be $\overline{pWind}_{p,s'} = \sum_{s\in S} P_s * pWind_{p,s}$ in this model. The mean-value programming TEP/GEP model is simply

$$\min_{DV} \sum_{(g,d)\in GCD} pInvCost_g * vNewGen_{g,d} + \sum_{(d,d')\in LC} pInvCost_{d,d'} * vNewLine_{d,d'} + \sum_{(p,rp)\in\Gamma_{rp,p},g,d,s'} pWeight_{rp} * [pFuelCost_t * vProd_{p,g,d,s'} + pENSCost * vPNS_{p,d,s'}] \quad (41)$$

subject to constraints (27)-(39). The set of operational scenarios S is implicitly replaced with the mean-value scenario $\{s'\}$ in all variables and constraints, and $pWind_{p,s}$ is replaced with its mean value $\overline{pWind}_{p,s'}$.

Minimum-Maximum Cost Robust Programming

Another widely used scenario-based planning technique is robust programming (here referred to as minimum-maximum cost robust programming), in which the maximum cost of the TEP/GEP solution under any future scenario is minimized. Robust techniques have the advantage of not requiring probability information about the future scenarios and so are perhaps more appropriate to apply when the scenarios represent specific future events. One disadvantage of minimum-maximum cost robust programming models is that their TEP/GEP solutions supposedly optimize for the "worst-case" or most expensive scenario in the scenario set, regardless of the likelihood of this scenario's occurrence.

Robust programming techniques seek to minimize the maximum cost or maximum regret of the second-stage operational variables in any scenario with respect to the first-stage decision variables. In this Section, we review the minimum-maximum cost formulation of robust programming.

The objective function of the minimum-maximum cost robust programming model is the following.

$$\min_{DV} \sum_{(g,d)\in GCD} pInvCost_g * vNewGen_{g,d} + \sum_{(d,d')\in LC} pInvCost_{d,d'} * vNewLine_{d,d'} + \max_{s}\{\sum_{(p,rp)\in\Gamma_{rp,p},g,d} pWeight_{rp} * [pFuelCost_t * vProd_{p,g,d,s} + pENSCost * vPNS_{p,d,s}]\} \quad (42)$$

This can easily be linearized by adding an auxiliary variable ζ to the objective function

$$\min_{DV} \sum_{(g,d)\in GCD} pInvCost_g * vNewGen_{g,d} + \sum_{(d,d')\in LC} pInvCost_{d,d'} * vNewLine_{d,d'} + \zeta \quad (43)$$

and adding a new constraint for each scenario

$$\sum_{(p,rp)\in\Gamma_{rp,p},g,d} pWeight_{rp} * [pFuelCost_t * vProd_{p,g,d,s} + pENSCost * vPNS_{p,d,s}] \le \zeta \forall s \in S \quad (44)$$

The model is therefore (43) subject to (27)-(39) and (44).

Minimum-Maximum Regret Robust Programming

A closely related technique is minimum-maximum regret robust programming, in which the maximum regret of the solution in any operational scenario is minimized. Regret of a TEP/GEP solution for scenario s is defined to be the difference between the solution's variable costs in this scenario, OC_s, and the variable costs of the perfect information TEP/GEP solution for this scenario OC_s^*. By the perfect information TEP/GEP solution for scenario s, we mean the solution of the deterministic or basic TEP/GEP model when it is known that only scenario s will occur, i.e. $S = \{s\}$. The minimum-maximum regret formulation does not necessarily plan for the worst-case scenario since its objective is to minimize the maximum cost *difference* between its solution and the "ideal" solution of each scenario.

The minimum-maximum regret robust programming objective function is

$$\min_{DV} \sum_{(g,d)\in GCD} pInvCost_g * vNewGen_{g,d} + \sum_{(d,d')\in LC} pInvCost_{d,d'} * vNewLine_{d,d'} + \max_s\{\sum_{(p,rp)\in\Gamma_{rp,p},g,d} pWeight_{rp} * [pFuelCost_t * vProd_{p,g,d,s} + pENSCost * vPNS_{p,d,s}] - OC_s^*\} \tag{45}$$

which can be linearized by adding the auxiliary variable ζ to the objective

$$\min_{DV} \sum_{(g,d)\in GCD} pInvCost_g * vNewGen_{g,d} + \sum_{(d,d')\in LC} pInvCost_{d,d'} * vNewLine_{d,d'} + \zeta \tag{46}$$

and adding a new constraint for each scenario

$$\sum_{(p,rp)\in\Gamma_{rp,p},g,d} pWeight_{rp} * [pFuelCost_t * vProd_{p,g,d,s} + pENSCost * vPNS_{p,d,s}] - OC_s^* \leq \zeta \forall s \in S \tag{47}$$

The model is therefore (46) subject to (27)-(39) and (47).

Design of Power System Model

The power system in our models has five nodes with electricity demand labeled nodes 1-5, and four nodes with no electricity demand but each with a candidate generator, labeled nodes 6-9. Nodes 1-5 are equipped with a set of existing thermal and wind generators and transmission lines. It is not guaranteed that the existing power system by itself is "feasible," in that the existing transmission/generation capacity is sufficient to meet demand at all nodes for all periods. The model allows investment in new wind generators and thermal generators (combined-cycle gas turbine plants) at nodes 6-9, as well as investment in new transmission to connect nodes 6-9 with the existing nodes with demand.

Nodes 6-9 are intended to represent candidate generation sites that are not already connected to the existing grid. Nodes 6 and 7 are intended to represent "nearby" generation sites with candidate transmission lines going to all 5 existing nodes. Nodes 8 and 9 represent more distant generation sites with higher transmission costs, and only have candidate transmission lines running to nodes 6 and 7. Therefore, candidate generators at nodes 8 and 9 can only be connected to the existing grid by constructing two transmission lines–one of which must run to node 6 or node 7 and the other from nodes 6 or 7 to the existing grid. Nodes 7 and 9 each have a candidate combined-cycle gas turbine (CCGT) generator, and nodes 6 and 8 each have a candidate wind farm. Furthermore, the fixed investment costs of the more distant candidate generators at nodes 8 and 9 are lower than those of their counterparts at nodes 6 and 7. This trade off may occur, for example, when the cost of land or construction is greater in more densely populated areas.

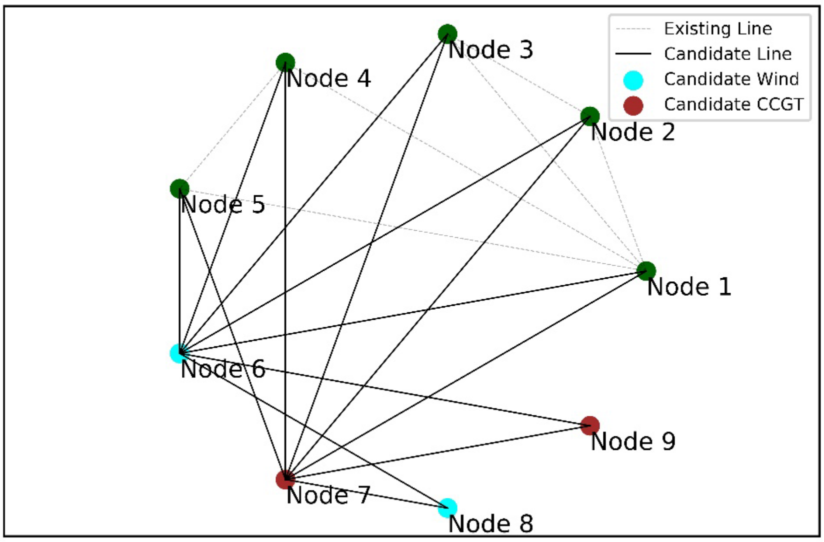


Figure 7: Depiction of the power system model network architecture.

The capacity of new investments is not limited ($vNewGen_{g,d} \in [0, \infty)$). See Figure 7 for a depiction of the full network, including both existing and candidate transmission lines and candidate generators.

Selection of Wind Capacity Factor Scenarios

Our models consider 10 scenarios for the hourly capacity factor of wind generators in the system. For the stochastic programming and mean-value models, we assume that the probability of each scenario is 1/10.

We downloaded 54 year-long 10-minute interval wind profiles (data for the theoretical production level of a 3 MW Vestas V90 wind turbine measured at a particular site at 10-minute intervals over a full year) from the National Renewable Energy Laboratory's Western Wind Integration data set. (*https://www.nrel.gov/grid/western-wind-data.html*). The sites chosen for the data collection represent various locations scattered throughout the Midwestern United States over several years. We randomly selected 10 of these 54 year-long wind power profiles as the data for the 10 scenarios. The peak values of the wind profiles were normalized to one, so that the data would effectively represent a capacity factor for wind generators. Because our models use one-hour time periods, we selected the subset of data points from the wind profiles corresponding to the beginning of each hour throughout the year. Sample one-day periods from the wind capacity factor scenarios are shown in Figure 8, as well as the entire set of 54 wind profiles.

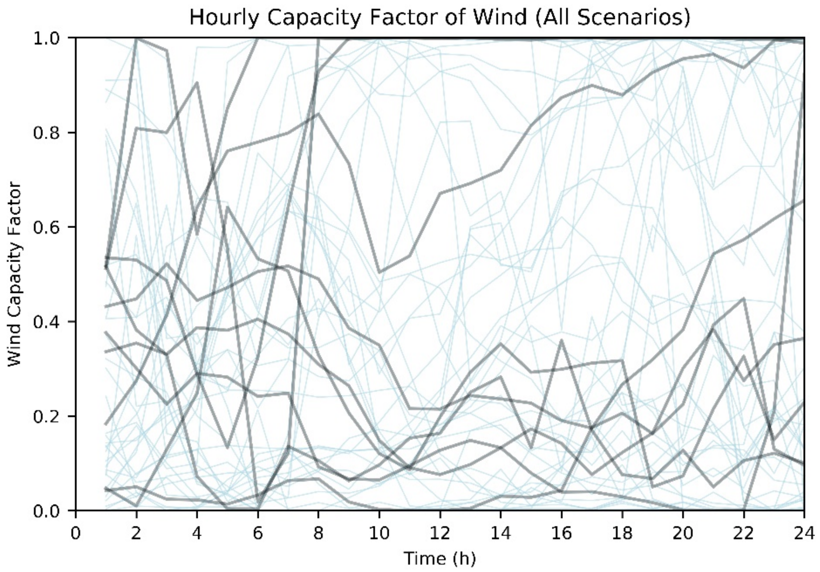


Figure 8: One-day samples of profiles of hourly capacity factor of wind for all possible scenarios, with selected (i.e. used-in-model) wind scenarios highlighted

Results

We have summarized our results in the following two ways: firstly, by directly comparing TEP/GEP solutions–i.e. the relative size of investments in new wind generation, thermal generation, and transmission capacity in the solutions of each of the scenario-based planning models Figure 9; secondly, by computing the mean out-of-sample variable costs of each model's TEP/GEP solutions Figure 8. We begin our discussion of the results by comparing the TEP/GEP solutions directly.

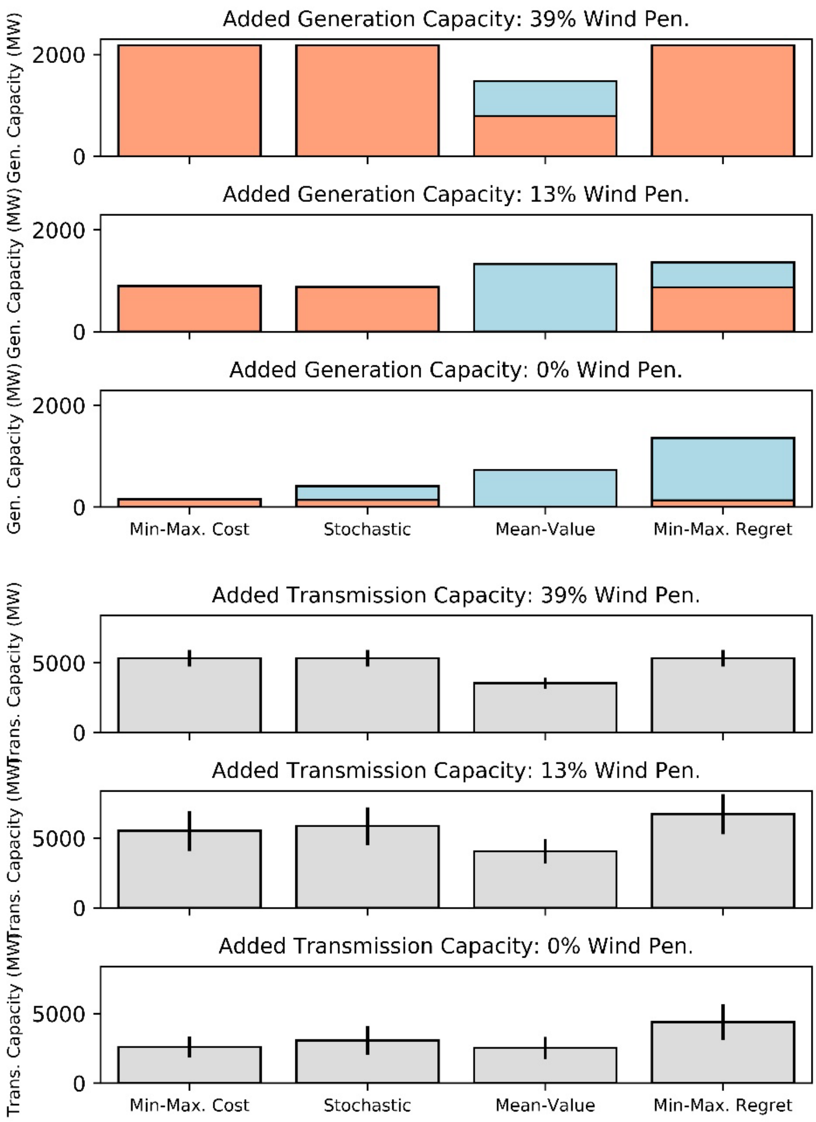


Figure 9: Transmission and generation capacity installation averaged across all demand cases for each wind penetration case and planning method.

In Figure 9 we observed that the mean-value programming model consistently invested in the most wind power capacity in all wind penetration cases, likely because the model represents the hourly capacity factor of wind power as the hourly capacity factor averaged over all 10 scenarios. Therefore, the variance of the hourly capacity factors in this model is decreased by a factor of 1/10 (and generally by a factor of $1/N$ for N scenarios), so the model underestimates the amount of grid flexibility required to deploy wind power. Hence, the model over-invests in wind power and under-invests in CCGT thermal generation, which is required to meet demand during periods of low wind availability. We therefore observed, Figure 10, that mean-value TEP/GEP solutions often resulted in load-shedding in the out-of-sample variable cost tests, resulting in higher variable costs on average.

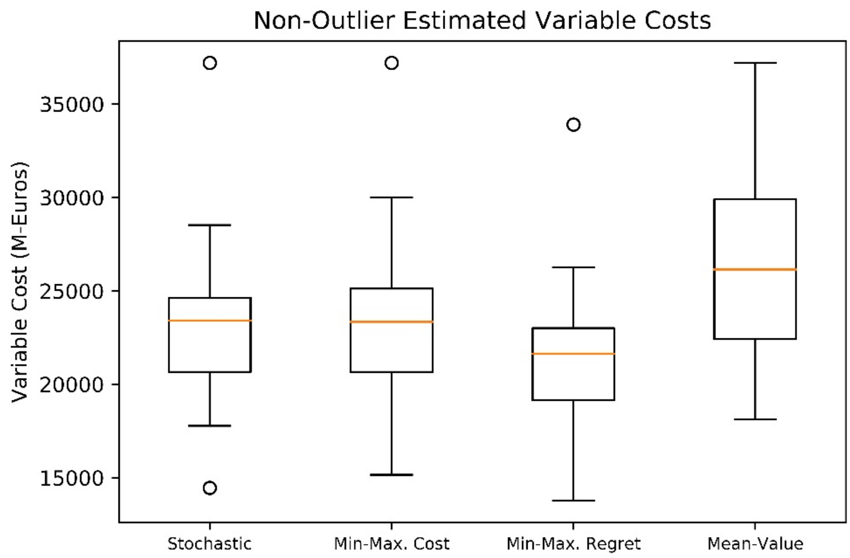


Figure 10:Box plot of average out-of-sample variable costs for each planning method and grid case.

As seen in Figure 9, the minimum-maximum cost robust programming model invested the most in new thermal generation and the least in new wind generation overall. These results likely reflect the model's tendency to plan for the "worst-case" cost scenario. In this case, the worst-case cost scenario is the one with the lowest average wind capacity factor (i.e. the least total available wind energy over the year), since wind energy is the least expensive source of energy in the model. In essence, the minimum-maximum cost model planned for the scenario in which the capacity factor of wind generation would be the lowest on average, so the model considered investments in wind generation to be less cost-effective than investments in CCGT thermal generation.

We observed also, in Figure 9, that the minimum-maximum regret robust programming model invested the most in new generation capacity overall, and the second most in new wind power capacity after mean-value programming. However, the mixture of new thermal and wind generation capacity in this model's solutions suggests that the solutions usually remain feasible (or at least do not result in load-shedding). The high investments in new generation capacity may be explained by considering that the model simultaneously optimizes for scenarios with lots of available wind energy and very little available wind energy–therefore, it invests in lots of wind power capacity to take advantage of the inexpensive power when it is available, and in lots of thermal generation capacity to avoid load-shedding when it is not.

The stochastic programming model also typically invested in a mixture of wind and thermal generation but invested in less total generation/transmission capacity overall. This might be explained because the minimum-maximum regret model invests in the most generation capacity because its objective function is the maximum of a set of "*distances*"– the distance of the current solution's variable costs from the perfect information variable costs of each scenario. Thus, if the variance of the scenarios is large (i.e. there are both high average capacity factor and low average capacity factor scenarios) then the planning solution must be such that the variable costs of the solution *in any scenario* can be very close to the perfect information variable costs of each scenario, meaning that it must construct lots of new wind generation for high-wind energy scenarios *and* lots of new thermal generation for low-wind energy scenarios. Stochastic programming, on the other hand, only considers the weighted sum of its variable costs in each scenario (weighted by the probability of each scenario), and is not concerned with being able to closely match the perfect information variable costs of each scenario, so it invests in less new generation in to reduce fixed costs.

Not surprisingly, therefore, we observed in Figure 10 that the minimum-maximum regret model's planning solutions had the lowest variable costs on average . The planning solutions of the stochastic programming model had the second lowest variable costs, followed by the minimum-maximum cost model (which did not invest in wind, and so could not take advantage of the zero-cost wind power in high capacity factor scenarios). The planning solutions of the mean-value programming model often resulted in load-shedding, and thus suffered large cost penalties in many scenarios. We consider this a major issue with the mean-value programming model. Some of the planning solutions are displayed in the power grid diagrams in Figure 11. Investments in new CCGT thermal generators are displayed in brown, and investments in new wind power generators are displayed in cyan. New transmission lines are represented by heavy black lines between nodes.

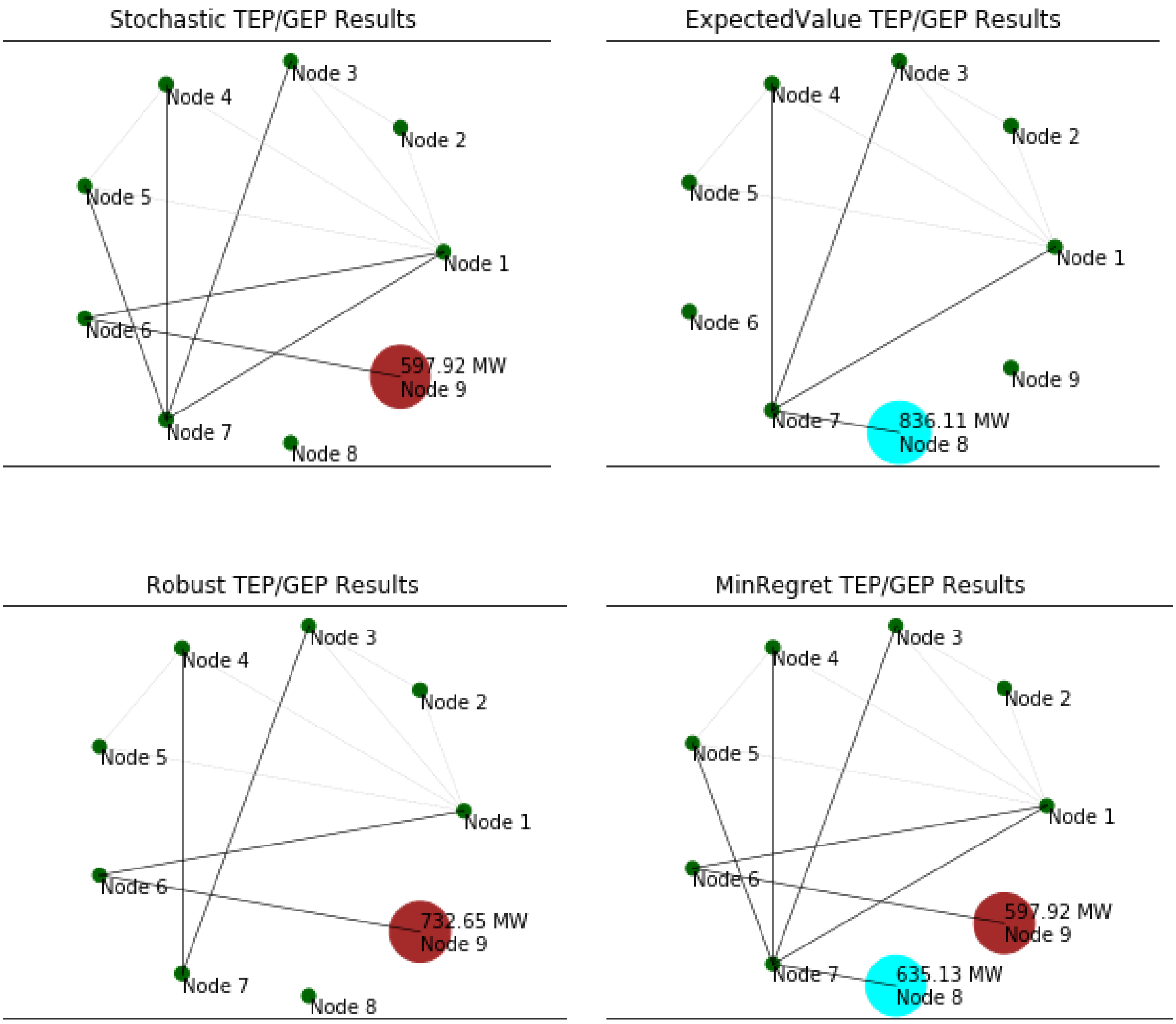


Figure 11: Diagrams of planning results for power grid with 13% wind penetration. Cyan-colored circles at nodes represent investments in new wind power generation. Brown-colored circles represent investments in new CCGT generators. Heavy black lines connecting nodes represent investments in new transmission lines.

Conclusions

Our goal was to understand the general behavior of each scenario-based power grid planning model under a variety of system conditions and remark on any interesting trends. Our results suggest the following conclusions about each of the model's performances, relative to one another:

- Mean-value programming models tend to underestimate the variance in the level of available wind power, and therefore invest the most in new wind generation and the least in new thermal generation

- Minimum-maximum cost robust programming models plan for the worst-case cost scenario, e.g. the scenario with the lowest capacity factor for new wind generation, and therefore invest the least in new wind generation and the most in new thermal generation

- Minimum-maximum regret robust programming models and stochastic programming models both invest in a mixture of new wind and thermal generation, especially in systems with low existing wind penetration (the 0% and 13% wind penetration cases). However, minimum-maximum regret models invest in more total generation capacity than stochastic programming models.

For future work we are interested to find out whether the addition of a wind curtailment penalty will reduce the size of wind investments in the minimum-maximum regret models. Furthermore, we are interested in studying these models in a greenfield setting (i.e. without any existing generation or transmission in the system), which would allow for easier interpretation of the planning results.

4 Transmission- and generation-expansion planning models for imperfectly competitive markets

This task focuses on the development of a mathematical bi-level model for transmission expansion planning for imperfectly competitive electricity markets. A first sub-task will be the development of a generation-expansion planning equilibrium model reflecting the potential exercise of market power, which will then be extended to a bi-level model including transmission investment in the upper level. Such a model accounts for the fact that transmission planning affects different agents in the electricity market (TSOs, MIs, GENCOs) that might have distinct and often conflicting objectives.

For example, a TSO might be interested in minimising system costs or maximising social welfare, whereas GENCOs mainly focus on maximising profits. Conventional transmission-expansion planning models, such as the one developed in Task 2.1, are not able to capture the game-theoretic interaction of opposing agents and are, thus, not suitable for assessing the potential effects of the exercise of market power on transmission-planning decisions. The game-theoretic model developed in this task adequately captures such interactions, thereby allowing for analyses able to support a transition to a low-carbon economy as envisaged by the SET-Plan. This first type of analysis will allow us to determine the extent to which existing least-cost models yield sub-optimal network expansion results due to the fact that they are disregarding strategic market behavior. This model will also shed light onto how different degrees of competition among power producers impact optimal transmission planning and on how the exercise of market power can be alleviated through improving the network, thereby potentially increasing the penetration of renewables.

4.1 Notation

The notation presented will be used used in Sections 4.2 y 4.3.

Sets / Indices

$y \in Y$	Year
$p \in P$	Periods (hours in the year)
$ps \in Ps$	Moving window periods
$rp \in RP$	Representative periods
$\Gamma_{rp,p}$	Set of correspondence between rp and p
p	Final period
$d, d' \in D$	Nodes
$g \in G$	Generator units
$t(g) \in T$	Thermal units
$w(g) \in W$	Wind generation
$h(g) \in H$	Storage units
$hf(h) \in HF$	Fast short-term storage units (batteries)
$hs(h) \in HS$	Slow long-term storage units (hydro)
$GAD(g, d)$	Set of all possible *g* located at node *d*
$GED(g, d)$	Set of existing g located at node *d*
$GCD(g, d)$	Set of candidate g located at node *d*
$LA(d, d')$	Set of all possible lines from node *d* to *d'*
$LE(d, d')$	Set of existing lines from node *d* to *d'*
$LC(d, d')$	Set of candidate lines from node *d* to *d'*
Hpp'	Univocal correspondence between perio*d p* and *p'* $\in \Gamma_{rp,p}$

Parameters

$pMaxProd_g$	Maximum capacity of technology g	MW
$pMaxFlow_{dd'}$	Maximum flow in line *dd'*	MW
$pReactance_{dd'}$	Reactance of line *dd'*	[p.u]
$pFCost_t$	Fuel cost of technology t	€/MWh
$pFixCost_t$	Fix operation cost of thermal generator	€
$pInvC_g$	Annualized investment cost g	€/MW
$pInvC_{dd'}$	Annualized investment cost of line *dd'*	€

$pDemand_{ypd}$	Demand Intercept at year *y* period p at node d	MW
$pDSlope$	Demand Slope	€/MW
$pEfficiency_{h}$	Efficiency of storage unit *h*	[p.u]
$pInfl_{yphsd}$	Energy inflows for year *y* period *p* storage *hs* at node d	MWh
$pMaxLevel_{h}$	Max reservoir level of storage unit *h*	MW
$pMinLevel_{h}$	Min reservoir level of storage unit *h*	MW
$pMaxCons_{h}$	Maximum consumption of storage unit	MW
M	Time window	h
pW_{rp}	Weight of each representative day	[p.u]
pSB	Base Power	MW
θ_{g}	Conjectural variation of GENCO *g*	€/MW
TC	Total Costs	€
LI	Line Investment Costs	€
GI	Generation Investment Costs	€
OC	Operation Cost	€
UD	Utility of the Demand	€

Variables

$vProd_{ywpgd}$	Production at year y period p of generator g at node *d*	MW
$vNewGen_{ygd}$	Investment status at year y of generation unit g at node d	{0,1}/MW
$vNewLine_{ydd'}$	Investment status at year y of line connecting node d to d'	{0,1}/MW
$vFlow_{ywpdd'}$	Flows at year y at period p from node *d* to *d'*	MW
$vTheta_{ywpd}$	Voltage angle at year *y* period *p* node *d*	p.u.
$vDemand_{ywpd}$	Demand at year y period p at d	MW
$vLevel_{ywphd}$	Level at year y period p of storage unit h at node d	MW
$vConw_{yphd}$	Consumption at year *y* period p of storage unit h at node d	MW
$vSpill_{ywphd}$	Spillage at year y period p of storage unit *h* at node d	MW
λ_{ypd}	Prices at year period *p* node *d*	€/MW
$vFlows_{ypdd'}$	Flows at year y at period p from node *d* to *d'*	MW
$\Delta Flows_{ypdd'}$	Flow step magnitude year y at period p from node *d* to *d'*	MW
$vBinFlow_{ypdd'k}$	Binary variable for flow at year y period p from node d to d'	{0,1}/MW
$vF\lambda_{ypdd'k}$	Flow times price at year y period p from node d to d' and step k	MW

4.2 Proactive Transmission Expansion Planning With Storage Considerations

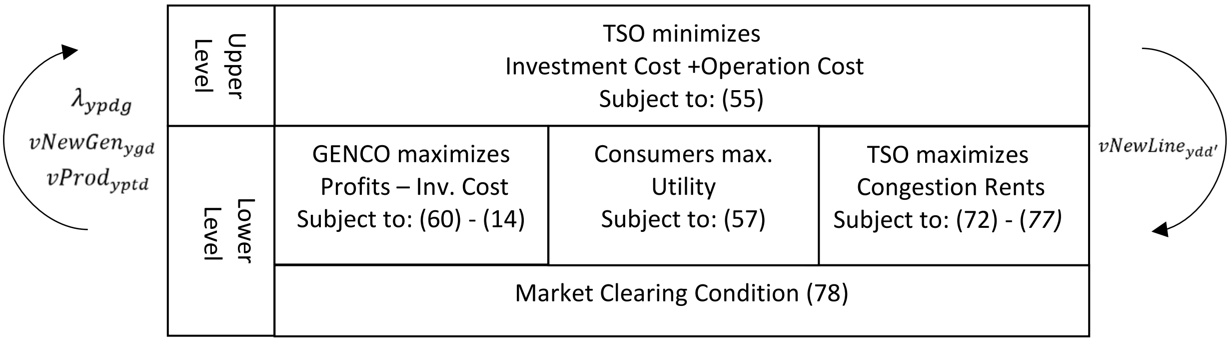
Under the current European deregulated market, centralized TSOs have to decide network investment by minimizing total operation cost (or maximizing total welfare), while decentralized GENCOs decide their expansion by maximizing their own profit. This process creates contradictory incentives that can result in a misalignment of short and long-term signals. Moreover, when the ideal cost-minimizing generation capacity investment assumed by the TSOs differs from reality, (due to strategic market interactions between GENCOs), then the transmission expansion plan could end up not being the cheapest option for society. The question that we try to answer in this paper is: if instead of assuming perfect competition a TSOs foresees strategic market outcomes, can this be beneficial for society? In order words, we want to analyze and compare, under a proactive framework approach, how the decisions of either perfect competition or Cournot in the operation and generation investment can affect the transmission decisions and the total welfare that the TSO aims to maximize.

For instance, if we consider that a TSOs takes its investment decision first, we would expect that, in order to achieve lower operation costs, a TSOs would invest as much as possible in transmission lines. This decision could be explained because, for the long-term, the magnitude of transmission investment is lower than generation investment. However, GENCOs might prefer lower investments in transmission capacity and higher investment in generation capacity in order to benefit from short-term price increases resulting from transmission congestions. These effects, in addition to the increasing penetration of renewable energy, storage and distributed generation, result in greater differences between short-term incentives (dependent on intermittency of renewable sources) and long-term decisions (dependent on seasonality). In this sense, we are interested in modeling how the competition in the electricity market affects and is affected by the long-term decisions in both generation and transmission expansion planning. Particularly, given that GENCOs interact with each other in a market driven framework while transmission is operated in a centralized way.

Moreover, we do not consider uncertainty in this paper. Conceptually speaking, introducing uncertainty would be a simple extension of our model, i.e. by means of stochastic programming for example. However, in our long-term investment problem we face different sources of uncertainty that can be either short long-term uncertainties, and that potentially should be addressed with different techniques such as robust optimization or stochastic programming in order to adequately capture to nature of each source of uncertainty (e.g. renewable production, policy decisions, price of fuels, demand evolution, etc.). However, this is out of the scope of this paper. In Section 0, the mathematical formulation of the one-level and bi-level models is presented. In Section 0, we present a study case to compare centralized and decentralized models. In Section 0, we conclude.

Proactive model formulation

In Section 0 we present the market responsive framework that is used to represent the distinctive degrees of competition in this proactive framework. Figure 12 shows the proposed framework, where TSO is in the Upper Level (see 0) and GENCOs are in the Lower Level (see 0). Then, in 0, the lower level is re-formulated as a set of non-linear equations by considering its Karush-Kuhn-Tucker (KKT) conditions. Finally, in 0, the structure of the linearized one-level proactive problem is presented, allowing us to solve this problem as a one-level Mixed Integer Linear Program (MILP).



Conjectured-Price Market

The market responsive framework, without the consideration of generation and transmission investment, is now formulated. We will follow the model proposed in [71]. For the sake of simplicity, we consider only one period, and only one GENCO per node. Considering one GENCO per node implies that the residual demand is seen by only one GENCO, and therefore each GENCO decides both price and quantity to be produced (considering transmission prices also, please see 0) as seen in as seen in [84], [88],[86]. Moreover, elasticity is assumed to be linear where *pDemand* represents the inelastic part of the demand and *pDslope* represents how it reacts to prices.

If demand is given by equation (48) and if every GENCO maximizes its profit as in (49), then market conditions are given by (50)

$$vDemand_d = pDemand_d - pDslope_d * vProd_{gad(g,d)} \; \forall g \tag{48}$$

$$Profit_g = \lambda_{gad(g,d)} * vProd_g - pFCost_g * vProd_g \;\; \forall g \tag{49}$$

$$\frac{\partial Profit_g}{\partial vProd_g} = \lambda_{gad(g,d)} + vProd_g * \frac{\lambda_{gad(g,d)}}{\partial vProd_g} - pFCost_g = 0 \;\; \forall g \tag{50}$$

Let us define $\theta_g = \frac{\partial \lambda}{\partial vProd_g}$ as the conjecture that is assumed to be known for every GENCO. *If* $\theta_g = 0$ we consider the Perfect Competition case (PC), and if $\theta_g = \frac{1}{pDSlope}$ we consider the Cournot Oligopoly case (CO).

Upper Level

The objective function (51) minimizes the investment cost in transmission lines (LI) and generation (GI) plus the total operation cost (OC). Each equation is defined for $p \in$

$\Gamma_{rp,p}$.(except 20). Please note $\Gamma_{rp,p}$ indicates, from the whole year, which are the hours that constitute each representative days. Equation (55) states that if a line is built, it will continue functioning during the time horizon.

$$\underset{vNewLineydd'}{\text{Minimize}} \quad GI + LI + OC \tag{51}$$

Subject to (52) - (55) , and Lower Level constraints.

$$GI := \sum_{gyd} (Y - y + 1) * pInvC_g \; * \left(vNewGen_{ygd} - \; vNewGen_{y-1,gd} \right) \tag{52}$$

$$LI := \sum_{ydd'} (Y - y + 1) * pInvL_{dd'} * \left(vNewLine_{ydd'} - vNewLine_{y-1,dd'} \right) \tag{53}$$

$$OC := \sum_{y,(p,rp) \in \Gamma_{rp,p},t,d} pW_{rp} * pFCost_t * vProd_{yptd} \tag{54}$$

$$vNewLine_{y-1,dd'} \leq vNewLine_{ydd'} \; \forall (d,d') \in LC \; \forall y \tag{55}$$

Lower Level: market equilibrium

This model considers the market clearing conditions, the usual operating constraints and a detailed storage operation modeling. At this level, we have both the market clearing and generation investment decisions. On the one hand, GENCOs seek to maximize benefits defined as Operation Incomes (OI) minus Operation Cost (OC) and Generation Investment (GI). On the other hand, the TSO wants to maximize congestions rents. We consider that both players act simultaneously on the lower level.

It is important to note that the lower level is single-level equilibrium model with two types of players (GENCOs, and, TSO) who take generation capacity investment and production decisions (GENCOs), and, corresponding power flow and voltage angle decisions (TSO) simultaneously. This implies that there is no anticipation of market outcomes in generation capacity decisions by GENCOs. In any case, since we are able to adapt the degree of competition in the market in our model, choosing a less competitive market might “compensate” for this non-anticipation [110]. Therefore, we consider a spatial equilibrium model where generators compete a la COURNOT and react naively to the transmission congestions as in [67]. This generalizes the work done in [111].

Finally, we assume that there is only one GENCO per node, but we might have several generation units per GENCO. Moreover, we consider only one unit per GENCO and thus index g represents both generators and company.

Consumer: Demand Utility maximization

The consumers try to maximize the utility of the demand, by deciding demand. Their optimization problem is given by:

$$Max_{vDemand_{ypd}} \sum_{y,(p,rp)\in\Gamma_{rp,p},d} pW_{rp} * \left(pDemand_{ypd} * vDemand_{ypd} - \frac{vDemand_{ypd}{}^{2}}{2}\right) \quad (56)$$

Subject to (57)

$$vDemand_{y,p,d} \geq 0 \qquad : \iota_{y,p,d} \quad \forall ypd \quad (57)$$

GENCO problem

The dual variables of each set of equations appear after colons.

$$arg \underset{LL}{\text{Maximize}}\, OI - OC - GI \quad (58)$$

$$LL := \{vNewGen_{ygd}, vProd_{ypgd}, vWind_{ypwd}, vCon_{yphd}, vSpill_{yphd}, vLevel_{yphd}\}$$

$$OI := \sum_{y,p,rp,g,d} pW_{rp} * (\lambda_{ywpd}) * (vProd_{ypgd\in GAD} - vCon_{yphd\in GAD}) \quad (59)$$

Subject to (52), (54), (59) , (60) - (14).

Equation *(78)* represents the nodal power balance (or market clearing condition) in which demand must equal local generation plus power inflows and minus power outflows. The dual variable λ_{ypd} related to this set of constraints correspond to the Locational Marginal Prices (LMP).

$$0 \leq vProd_{ypgd} \leq pMaxProd_{g} \qquad : \bar{\rho}_{ypgd}, \ \underline{\rho}_{ypgd} \quad \forall yp, \forall gd \in GED \quad (60)$$

$$0 \leq vWind_{ypwd} \leq pMaxWind_{pwd} \qquad : \overline{\rho w}_{ypwd}, \underline{\rho w}_{ypwd} \quad \forall yp, \forall wd \in GED \quad (61)$$

$$0 \leq vProd_{ypgd} \leq pMaxProd_{g} * vNewGen_{ywd} \qquad : \bar{\omega}_{ypgd}, \ \underline{\omega}_{ypgd} \quad \forall yp, \forall gd \in GCD \quad (62)$$

$$0 \leq vWind_{ypwd} \leq pMaxWind_{pwd} * vNewGen_{ywd} : \overline{\omega w}_{ypwd}, \underline{\omega w}_{ypwd} \quad \forall yp, \forall wd \in GCD \quad (63)$$

$$0 \leq \frac{vCon_{yphd}}{pEfficiency_{h}} \leq pMaxCons_{h} \qquad : \overline{\kappa e}_{yphd}, \underline{\kappa e}_{yphd} \quad \forall yp, \forall hd \in GED \quad (64)$$

$$0 \leq \frac{vCon_{yphd}}{pEffic_{h}} \leq pMaxLevel_{h} * ETD * vNewGen_{yhd} : \overline{\kappa c}_{yphd}, \underline{\kappa c}_{yphd} \quad \forall yp, \forall hd \in GCD \quad (65)$$

$$-vNewGen_{y-1,gd} + vNewGen_{ygd} \geq 0 \qquad : \underline{\beta}_{ygd} \quad \forall ygd \quad (66)$$

$$0 \geq -vNewGen_{ygd}; 0 \leq MaxGen_g - vNewGen_{ygd} \quad : \bar{o}_{ygd}, \underline{o}_{ygd} \qquad \forall y, \forall gd \in GCD \tag{67}$$

$$pMinLevel_h \leq vLevel_{yphd} \leq pMaxLevel_h \quad : \overline{\mu e}_{yphd}, \underline{\mu e}_{yphd} \qquad \forall yp, \forall hd \in GED \tag{68}$$

$$0 \leq vSpill_{yphd} \quad : \varepsilon_{yphd} \qquad \forall yp, \forall hd \in GAD \tag{69}$$

$$vLevel_{yph_fd} = vLevel_{y,p-1,hf,d} + pIniLevel_{y=1,p=1,hf,d} - vProd_{yph_fd} + vCon_{yph_fd} \quad : \psi_{yphd} \qquad \forall h_f d \in GAD, \forall yp, p < pf \tag{70}$$

$$vLevel_{ywphsd} = vLevel_{y,w,p-M,hs,d} + pIniLevel_{y=1,p=1,hs,d} + \sum_{p'}^{p} \sum_{p''} (pInfl_{ywp''hsd} - vSpill_{ywp''hsd} - vProd_{ywp''hsd} + vCon_{ywp''hsd}) \quad : \psi'_{yphd} \qquad \forall hs, d \in GAD, \forall yp, p < pf \tag{71}$$

Equations (60), (64), (72), (67)-(69) represent upper and lower bounds of the existing elements of the system. While equations (62) and (65) represent the lower bounds of the candidate new elements in the system. Equations (72) and (73) represent the DC formulations of the network for existing lines, while equations (74) - (77) represent the DC formulations for new lines. In (74) - (77), a Big M approach has been used to linearize the product between investment decisions and angles. Finally, equations (13) and (14) represent the storage balance conditions as proposed in [109]. On the one hand, equation (14) is considered for long-term storage i.e. hydro when only interday balance is considered. With this equation, reservoir management is followed up across the entire year, as opposed to the rest of constraints in which only intraday operations are included. For the hydro case the parameter pInflow represents the water inflows in the year (in energy), vCon represents pumping decisions and vProd the production decisions of the hydro unit. On the other hand, equations (14) and (13) are jointly considered to represent short-term storage when intraday operation is relevant i.e. batteries. In this case, we do a daily energy balance of the battery but also a i.e weekly balance to consider the transition between the representative days. For batteries, pInflow is set to 0, and vCon and vProd represent charging and discharging of the battery. While the detailed formulation and explanation of this representation of storage is presented in [23], we briefly explain it here for clarity.

The reservoir energy balance is verified for a given time window. For instance, consider 4 representative periods, a 168 hour (one week) window and two weeks as shown in Figure 13. Thus, the reservoir balance equation (14) will be verified at the end of every week e.g. at M1 and M2. Thus, the interday balance is the sum of inflows and consumption minus spillage and production for every "representative hour" (p''), which represents each hour of the year (p'). In addition, they are summed over the window M until hour ($p \in Ps$). Please note that $H(p'', p')$ maps each hour of the year to its corresponding hour in the appropriate representative day (i.e the first 24 hours of the year can be represented by hours 5545-5568 of RP4), and is not to be confused with

$\Gamma_{rp,p}$ that tells us which hours of the year are the representative ones (i.e RP4 is made of hours 5545-5568).

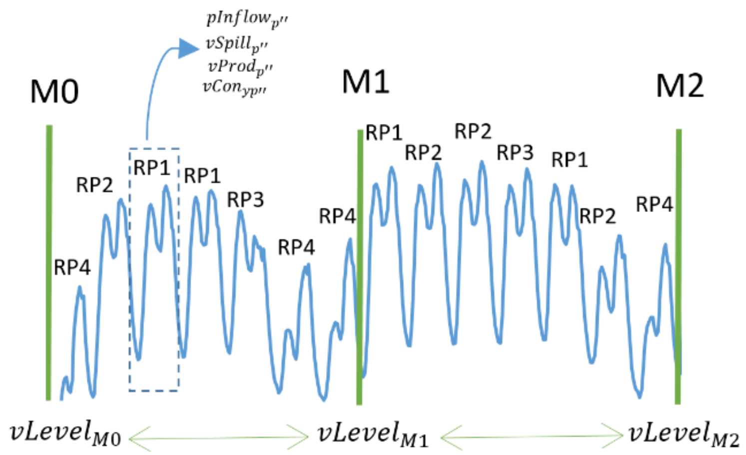


Figure 13: Interday Energy Balance

TSO problem

We assume that the (TSO) that wants to maximize congestions rents from price differences.

$$arg \underset{vFlows_{ypdd'},vTheta_{ypd}}{\text{Maximize}} \sum_{y,p,d} (\lambda_{ypd\in(GAD)} - \lambda_{ypd'\in(GAD)}) * vFlows_{ypdd'}$$

s.t

$$pMaxFlows_{dd'} \geq vFlows_{ypdd'} \geq -pMaxFlows_{dd'} : \bar{\phi}_{ypdd'}, \underline{\phi}_{ypdd'} \forall (d,d') \in LE, \forall yp \quad (72)$$

$$vFlows_{ypdd'} = pSB * \frac{vTheta_{ypd} - vThetha_{ypd'}}{pReactance_{dd'}} \quad : \phi_{ypdd'} \quad \forall (d,d') \in LE, \forall yp \quad (73)$$

$$vFlows_{ypdd'} \geq -pMaxFlows_{dd'} * vNewLine_{ydd'} \quad : \underline{\zeta}_{ypdd'} \quad \forall (d,d') \in LC, \forall yp \quad (74)$$

$$-vFlows_{ypdd'} \geq -(\ pMaxFlows_{dd'} * vNewLine_{ydd'}\ ) : \bar{\zeta}_{ypdd'} \quad \forall (d,d') \in LC, \forall yp \quad (75)$$

$$-vFlows_{ypdd'} \geq \left(-pSB * \frac{vTheta_{ypd} - vThetha_{ypd'}}{pReactance_{dd'}} - pMaxFlows_{dd'}(1 - vNewLine_{ydd'})\right) \quad (76)$$
$$: \bar{\tau}_{ypdd'} \quad \forall (d,d') \in LC, \forall yp$$

$$vFlows_{ypdd'} \geq \left(pSB * \frac{vTheta_{ypd} - vThetha_{ypd'}}{pReactance_{dd'}} - pMaxFlows_{dd'}(1 - vNewLine_{ydd'}) \right) \quad (77)$$
$$: \underline{\tau}_{ypdd'} \qquad \forall (d,d') \in LC, \forall yp$$

Market Clearing

$$\sum_{g\epsilon GAD} vProd_{ypgd} + \sum_{g\epsilon GAD} vWind_{ypgd} + \sum_{d'\epsilon LA} vFlows_{ypdd'} - \sum_{d'\epsilon LA} vFlows_{ypd'd} + \sum_{g\epsilon GAD} \frac{vCon_{yphd}}{pEfficiency_{h\epsilon GHD}} = pDemand_{ypd} \quad : \lambda_{ypd} \quad \forall y,p,d \quad (78)$$

The simultaneous consideration of the GENCO, TSO, and market clearing condition represent the wholesale market for the case of perfect and imperfect competition (depending on the conjectural variation described in 0).

KKT Conditions

An equivalent formulation for the lower level optimization problem is presented. KKT conditions are the following:

- Primal feasibility conditions. TSO: (72) - (77) MC: (78) Gencos: (60) - (14)
- Dual feasibility conditions. TSO: (79) - (80) and Gencos: (81) - (87)
- Complementary slackness conditions[26]

Dual feasibility conditions: (Each equation is defined for $p \in \Gamma_{rp,p}$, except for equations

(83) to (87).

$$\phi_{ypdd'\in LE(d,d')} + \underline{\phi}_{ypdd'\in LE(d,d')} - \bar{\phi}_{ypdd'\in LE(d,d')} + \underline{\zeta}_{ypdd'\in LC(d,d')} - \bar{\zeta}_{ypdd'\in LC(d,d')} + \bar{\tau}_{ypdd'\in LC(d,d')} - \underline{\tau}_{ypdd'\in LC(d,d')} + \lambda_{ypd'\in(GAD)} - \lambda_{ypd\in(GAD)} = 0 \quad : vFlows_{ypdd'} \ \forall ypdd' \quad (79)$$

$$\sum_{d\in LE(d,d')} \frac{pSB}{pReactance_{dd'}} * \phi_{ypdd'} - \sum_{d'\in LE(d,d')} \frac{pSB}{pReactance_{d'd}} * \phi_{ypd'd} + \sum_{d\in LC(d,d')} \frac{pSB}{pReactance_{dd'}} * \bar{\tau}_{ypdd'} - \sum_{d'\in LC(d,d')} \frac{pSB}{pReactance_{dd'}} * \underline{\tau}_{ypd'd} - \sum_{d'\in LC(d',d)} \frac{pSB}{pReactance_{d'd}} * \bar{\tau}_{ypd'd} + \sum_{d\in LC(d,d')} \frac{pSB}{pReactance_{d'd}} * \underline{\tau}_{ypdd'} = 0 \ : \ vTheta_{ypd}, \forall ypd \quad (80)$$

[26] Linearized conditions can be found in ANNEX

$$\sum_{gyd}(Y-y+1)*pInvC_g+\sum_{gyd}(Y-y+1)*pInvC_g+pMaxProd_g*\bar{\omega}_{ypgd}+\underline{\beta}_{ygd} - \underline{\beta}_{y+1,gd} - \bar{o}_{ygd}+\underline{o}_{ygd} \quad =0 : vNewGen_{ygd} \;\; \forall ygd \in GCD \tag{81}$$

$$-vDemand_{ypd}+pDemand_d-pSlope*vProd_{yptd}=0 : vDemand_{ypd} \;\; \forall ygd \in GAD \tag{82}$$

For equations

(83) to (87) we define $p''=p'+1-M$ $Pa=\{p|p \in \Gamma_{rp,p}\}$, $Ps=\left\{ps|\frac{ps}{M}\in Z^+\right\}$, $and\ Pt=Ps\cup Pa$

$$\left(\sum_{y,(p,rp)\in\Gamma_{rp,p},d} pW_{rp}*(-FuelCost_{tp}+vProd_{yptd}*\frac{\partial\lambda_{ypd\in(GAD)}}{\partial vProd_{yptd_g}})\right)+\lambda_{ypd\in(GAD)} - \bar{\rho}_{ypgd\in(GED)}+\underline{\rho}_{ypgd\in(GED)}-\bar{\omega}_{ypgd\in(GCD)}+\underline{\omega}_{ypgd\in(GED)} + \sum_{p''}^{p'}(\psi_{yph})=0 \tag{83}$$

$$: vProd_{ypgd} \quad \forall y,hd \in (GED)\ \forall p' \in H(p',p)\ /\ \ p\in Pa,\ p' \in Ps$$

$$\bar{\kappa}_{yphd}-\underline{\kappa}_{ygphd}+\psi_{yph_fd}+\sum_{p''}^{p'}\left(\psi'_{yph}\right)=0 \tag{84}$$

$$: vCon_{yphd} \quad \forall p' \in H(p',p), p\in Pa,\ p' \in Ps, \forall y,hd \in (GED)$$

$$-\bar{\mu}_{yphd}+\underline{\mu}_{yphd}+\sum_{p''}^{p'}\psi_{yph}=0$$

$$: vSpill_{yphd} \quad \forall p' \in H(p',p)\ \ p\in Pa,\ p' \in Ps, \forall y,hd \in (GED) \tag{85}$$

$$\lambda_{ypd\in(GAD)}+\overline{\rho w}_{ypgd},\underline{\rho w}_{ypgd} \quad \forall ypwd \in (GED) \tag{86}$$

$$-\bar{\mu}_{yphd}+\underline{\mu}_{yphd}+\psi_{yp\in Pa,h_fd}+\psi_{y,p+1\in Pa,h_fd}+\psi'_{yp\in Ps,hd}-\psi'_{y,p+M|p\in Ps,hd}=0 \tag{87}$$

$$: vLevel_{yphd} \forall p \in Pt, \forall yhd \in GED$$

Please note that all the previous equations are linear, therefore the only nonlinearities are those introduced by the complementarity conditions. Consequently, this set of KKT conditions can be solved either as an NLP or formulated and solved as an MPEC. Nevertheless, we can only guarantee to find a local optimum when solving NLP or MPEC and, in some cases, no solution might be found. In order to tackle the limitations of this approach, a bi-level MILP problem is formulated to obtain a global optimum solution.

Linearized Complementarities

Each set of equation corresponds to the linearization of a complementarity condition. Please note that equality constrains do not need a complementarity condition. We denote $\overline{Mdual}, \underline{Mdual}$ as the big M parameters corresponding to each dual variable for upper and lower bounds respectively. $\overline{Ydual}, \underline{Ydual}$ refer to binary variables corresponding to each dual variable for upper and lower bounds respectively. Additionally, we implement a regularization method to compute Big Ms as proposed in [100].

$$
\begin{array}{c}
vProd_{ypgd} \leq \underline{M\rho} * \underline{Y\rho}_{ypgd} \\
\underline{\rho}_{ypgd} \leq \underline{M\rho} * \left(1 - \underline{Y\rho}_{ypgd}\right) \\
vProd_{ypgd} - pMaxProd_{g} \leq \overline{M\rho} * \overline{Y\rho}_{ypgd} \\
0 \leq \bar{\rho}_{ypgd} \leq \overline{M\rho} * \overline{Y\rho}_{ypgd}
\end{array}
\qquad \forall gd \in GED, \ \forall yp \qquad (88)
$$

$$
\begin{array}{c}
Wind_{ypwd} \leq \underline{M\rho w} * \underline{Y\rho w}_{ypwd} \\
\underline{\rho w}_{ypwd} \leq \underline{M\rho w} * \left(1 - \underline{Y\rho w}_{ypgd}\right) \\
\overline{\rho w}_{ypgd} \leq \overline{M\rho w} * \overline{Y\rho w}_{ypwd} \\
Wind_{ypwd} - pMaxWind_{wp} \leq \overline{M\rho w} * \overline{Y\rho}_{ypwd}
\end{array}
\qquad \forall wd \in GED, \ \forall yp \qquad (89)
$$

$$
\begin{array}{c}
0 \leq vProd_{ypgd} \leq \underline{M\omega} * \underline{Y\omega}_{ypgd} \\
0 \leq \underline{\omega}_{ypgd} \leq \underline{M\omega} * (1 - \underline{Y\omega}_{ypgd}) \\
vProd_{ypgd} - pMaxProd_{g} * vNewGen_{ygd} \leq \overline{M\omega} * \overline{Y\omega}_{ypgd} \\
\overline{\omega}_{ypgd} \leq \overline{M\omega} * \overline{Y\omega}_{ypgd}
\end{array}
\qquad \forall gd \in GCD, \ \forall yp \qquad (90)
$$

$$
\begin{array}{c}
vWind_{ypwd} - pMaxWind_{pwd} * vNewGen_{ywd} \leq \underline{M\omega w} * \underline{Y\omega w}_{ypwd} \\
\underline{\omega w}_{ypwd} \leq \underline{M\rho w} * \left(1 - \underline{Y\omega w}_{ypwd}\right) \\
\overline{\rho w}_{ypgd} \leq \overline{M\rho w} * \overline{Y\rho w}_{ypgd} \\
Wind_{ypwd} - pMaxWind_{wp} \leq \overline{M\rho w} * \overline{Y\rho}_{ypwd}
\end{array}
\qquad \forall wd \in GCD \ \forall yp \qquad (91)
$$

$$
\begin{array}{c}
pMinLevel_{h} - vLevel_{yphd} \leq \underline{M\mu e} * \underline{Y\mu e}_{yphd} \\
\underline{\mu e}_{yph} \leq \underline{M\mu e} * (1 - \underline{Y\mu e}_{yphd}) \\
vLevel_{yphd} - pMaxLevel_{h} \leq \overline{M\mu e} * \overline{Y\mu}_{yphd} \\
\overline{\mu e}_{yph} \leq \overline{M\mu} * (1 - \overline{Y\mu}_{yphd})
\end{array}
\qquad \forall gd \in GED, \ \forall yp \qquad (92)
$$

$$
\begin{array}{c}
pMinLevel_{h} \leq \underline{M\mu c} * \underline{Y\mu c}_{yphd} \\
\underline{\mu c}_{yph} \leq \underline{M\mu c} * (1 - \underline{Y\mu c}_{yphd}) \\
vLevel_{yphd} - pMaxProd_{h} * ETD * vNewGen_{yhd} \leq \overline{M\mu c} * \overline{Y\mu}_{yphd} \\
\overline{\mu c}_{yph} \leq \overline{Mc} * (1 - \overline{Y\mu}_{yphd})
\end{array}
\qquad \forall gd \in GCD, \ \forall yp \qquad (93)
$$

$$\begin{aligned}
\frac{vCon_{yphd}}{pEfficiency_h} &\le \underline{M\kappa e} * \underline{Y\kappa e}_{ypgd} \\
\underline{\kappa e}_{yhpd} &\le \underline{M\kappa e} * (1 - \underline{Y\kappa e}_{ypgd}) \\
\frac{vCon_{yphd}}{pEfficiency_h} - pMaxCons_h &\le \overline{M\kappa e} * \overline{Y\kappa e}_{ypgd} \\
\bar{\kappa}_{yhpd} &\le \overline{M\kappa} * (1 - \overline{Y\kappa}_{ypgd})
\end{aligned} \qquad \forall hd \in GED, \ \forall yp \qquad (94)$$

$$\begin{aligned}
\frac{vCon_{yphd}}{pEfficiency_h} &\le \underline{M\kappa c} * \underline{Y\kappa c}_{ypgd} \\
\underline{\kappa c}_{yhpd} &\le \underline{M\kappa c} * (1 - \underline{Y\kappa c}_{ypgd}) \\
\frac{vCon_{yphd}}{pEfficiency_h} - pMaxLevel_h * ETD * vNewGen_{yhd} &\le \overline{M\kappa c} * \overline{Y\kappa c}_{ypgd} \\
\bar{\kappa}_{yhpd} &\le \overline{M\kappa c} * (1 - \overline{Y\kappa c}_{ypgd})
\end{aligned} \qquad \forall gd \in GCD, \ \forall yp \qquad (95)$$

$$\begin{aligned}
-vNewGen_{y-1,gd} - vNewGen_{ygd} &\le \underline{M\beta} * \underline{Y\beta}_{ygd} \\
\underline{\beta}_{ygd} &\le \underline{M\beta} * (1 - \underline{Y\beta}_{ygd})
\end{aligned} \qquad \forall gd \in GCD, \ \forall yp \qquad (96)$$

$$\begin{aligned}
vNewGen_{ygd} &\le \underline{Mo} * \underline{Yo}_{ygd} \\
\bar{o}_{ygd} &\le \underline{Mo} * (1 - \underline{Yo}_{ygd}) \\
MaxGen_g - vNewGen_{ygd} &\le \underline{Mo} * \underline{Yo}_{ygd} \\
\bar{o}_{ygd} &\le \overline{Mo} * (1 - \overline{Yo}_{ygd})
\end{aligned} \qquad \forall gd \in GCD, \ \forall yp \qquad (97)$$

$$\begin{aligned}
-vFlows_{ypdd'} + pMaxFlows_{dd'} &\le \underline{M\phi} * \underline{Y\phi}_{ypdd'} \\
\underline{\phi}_{ypdd'} &\le \underline{M\phi} * (1 - \underline{Y\phi}_{ypdd'}) \\
-vFlows_{ypdd'} - pMaxFlows_{dd'} &\le \overline{M\phi} * \overline{Y\phi}_{ypdd'} \\
-vFlows_{ypdd'} - pMaxFlows_{dd'} &\le \overline{M\phi} * (1 - \overline{Y\phi}_{ypdd'})
\end{aligned} \qquad \forall (d,d') \in LE, \ \forall yp \qquad (98)$$

$$\begin{aligned}
vFlows_{ypdd'} + pMaxFlows_{dd'} * vNewLine_{ydd'} &\le \underline{M\zeta} * \underline{Y\zeta}_{ypdd'} \\
\underline{\zeta}_{ypdd'} &\le \underline{M\zeta} * (1 - \underline{Y\zeta}_{ypdd'})
\end{aligned} \qquad \forall (d,d') \in LC, \ \forall yp \qquad (99)$$

$$\begin{aligned}
-vFlows_{ypdd'} + \left(pMaxFlows_{dd'} * vNewLine_{ydd'} \right) &\le \overline{M\zeta} * \overline{Y\zeta}_{ypdd'} \\
\bar{\zeta}_{ypdd'} &\le \overline{M\zeta} * (1 - \overline{Y\zeta}_{ypdd'})
\end{aligned} \qquad \forall (d,d') \in LC, \ \forall yp \qquad (100)$$

$$\begin{aligned}
-vFlows_{ypdd'} + \left(\begin{matrix} pSB * \dfrac{vTheta_{ypd} - vThetha_{ypd'}}{pReactance_{dd'}} \\ + pMaxFlows_{dd'}\left(-1 + vNewLine_{ydd'}\right) \end{matrix} \right) &\le \overline{M\tau} * \overline{Y\tau}_{ypdd'} \\
\bar{\tau}_{ypdd'} &\le \overline{M\tau} * (1 - \overline{Y\tau}_{ypdd'})
\end{aligned} \qquad \forall (d,d') \in LC, \ \forall yp \qquad (101)$$

$$\begin{aligned}
vFlows_{ypdd'} + \left(\begin{matrix} -pSB * \dfrac{vTheta_{ypdd'} - vThetha_{ypdd'}}{pReactance_{dd'}} \\ - pMaxFlows_{dd'}\left(1 - vNewLine_{ydd'}\right) \end{matrix} \right) &\le \underline{M\tau} * \underline{Y\tau}_{ypdd'} \\
\underline{\tau}_{ypdd'} &\le \underline{M\tau} * (1 - \underline{Y\tau}_{ypdd'})
\end{aligned} \qquad \forall (d,d') \in LC, \ \forall yp \qquad (102)$$

MILP formulation

After taking the KKT conditions of the lower level and linearizing the complementarity conditions we end up with MIP problem which can be solved by commercial softwares. These complete problem is therefore composed of the following equations:

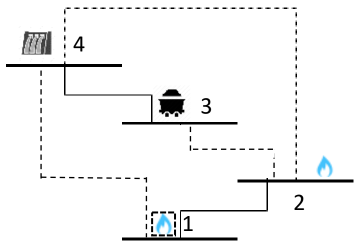
Objective function (51)	
Subject to:	
Upper level constraints:	(52) - (55)
Primal feasibility constraints:	(60) - (14)
Dual feasibility constraints:	(79) - (87)
Linearized complementarities:	(89) - (102)

Case Study

In this Section we present an illustrative case study, in Section 0 we present the data of our illustrative system, in Section 0 we present the market operation and capacity expansion results and finally, in Section 0 we investigate the results for storage technologies.

Data

The system as shown in Figure 14, is composed of 4 nodes, with demand in each node. We consider 3 generation companies (C2, C3, C4), 3 existing generators, and 2 candidate generators for companies C2 and C3 (candidate generator in node 1 belongs to C3 and candidate generator in node 2 belongs to company 2).



Node	Max/Min (MWh)	GENCO (g, tec)	Fuel Cost (€/MWh)	Capacity (MW)
1	572/303	(C2,CCGT)	31	550
2	286/151	(C3,Coal)	54	588
3	429/227	(C4,Hydro)	0	500
4	429/227	-		

	Reservoir (GWh)		Inflows (MWh)	
	Max	**Min**	**Max**	**Min**
Hydro	240	60	0.8	0.1

Figure 14: System Characteristics

For the network configuration, we consider two scenarios: Green-Field Scenario (GF): In this scenario, we assume that no network is in place and investments have to be done from scratch. Brown-Field Scenario (BF): In this scenario, we have the network depicted in Figure 14. Therefore, we have 2 existing and 3 candidate lines. Continuous lines in Figure 14 represent existing units and existing transmission lines. Dotted lines represent candidate units and candidate transmission lines. We also include fuel cost and capacity of the existing generators. Additionally, for the hydro unit we have the maximum and minimum reserve levels of the hydro reservoir as well and the maximum and minimum hourly inflows into the reservoir. Finally, to keep this case study simple we disregard wind spillages and we consider a net total demand.

In Table XIV and Table XV we can find the operation and investment cost of candidate units and lines (we include all lines as candidates for GF case) as well as their location and maximum capacity. Additionally, for this study case, 4 representative days (24 hours each) are chosen, a window of 168 h is selected and the model is run for a 1-year horizon. We chose 4 days based on the study done in [45], where a comparison of CPU time compared to objective function error was done for a different number of representative days. Compared to their study we chose less days because of the complexity introduced by Big-M constraints into bi-level models. Additionally, the model is generic and can be solved for a multi-year horizon, however, given the complexities of bi-level models and the new formulation for long and short-term storage, we decided to consider only 1 year to focus in depth on the basic planning results.

Table XIV: Candidate Lines

From Node	To Node	Reactance [p.u]	Annual Inv Cost (M€)	Capacity (MW)
3	4	0.03	0.375	200
1	2	0.03	0.375	200
1	4	0.03	0.375	200
2	3	0.03	0.375	200
2	4	0.03	0.375	200

Table XV: Candidate Generators

(G, TEC)	Node	Annual Inv Cost [k€/MW]	Fuel Cost (€/MWh)	Capacity (MW)
(C2,CCGT)	2	29	27	667
(C3,CCGT)	1	40	28	500

Additionally, we consider two different competition cases both from GF and BF scenarios. We consider the Perfect Competition (PC) case with $\theta_g = 0$ and the Cournot Oligopoly (CO) case with $\theta_g = 0.008$, please see Section 0. The model is coded in GAMS, solved with GUROBI and run on a computer with 3.4 GHz processor and 32 GB of RAM. For the GFS the PC case takes 145 s and the CO case 2000 s with a 0% integrality gap. For the BF case the PC model takes 969s and CO takes 1158s for a 1% integrality gap[27].

Operation and Investment Results

First, we analyze investment decisions. *Table XVI* and

Table XVII show transmission and generation capacity expansion. First of all, we observe that the degree of competition in the market affects optimal TEP decisions. This indicates that a bi-level model provides insights that a single-level model is not able to yield. Moreover, in *Table XVI* and

Table XVII we can see that for both GF and BF scenarios capacity expansion is higher in the PC case compared to the CO case. This is reasonable because, in a perfectly competitive environment, GENCOs cannot react strategically because they do not have market power and therefore the TSO tends to overinvest to guarantee lower operational costs. Inversely, in a Cournot oligopoly framework, GENCOs have market power and tend to underinvest in order to increase their profits, a phenomenon observed often [110],[111]. Please note that in the CO case the generator at node 1 remains isolated, this is a direct consequence of the elasticities chosen at each node. If a less elastic demand was chosen at node 1, the model would decide to connect it to the network. Below we will analyze system costs and efficiency by introducing the welfare measure.

Table XVI: Transmission Expansion

		Lines Invested	Capacity (MW)	Annual Inv Cost (M€)
GF	PC	(2-4) (3-2) (3-4)	600	0.37
	CO	(3-2)(3-4)	400	0.75

[27] The window highly affects computational time. For BF case we set a 85 hours window, and program runs for 10000 s with only a 5% gap.

BF	PC	(2-4) (3-2)	400	0.75
	CO	(3-2)	200	0.37

In order to analyze the efficiency of each framework we use the welfare. We compute the Social Welfare as the summation of the Consumer Surplus (CS) and the Producer Surplus (PS). Please note that the calculation of the CS is the usual expression that results from the integral of the utility of the demand.

$$CS = \sum_{A} \frac{pDemand}{pSlope} vProd_{yptd} - \frac{1}{2pSlope} * vProd_{yptd}{}^{2} - \lambda_{ypd(GAD)} * vProd_{yptd} \quad (103)$$

$$\begin{aligned} PS = \sum_{A} \lambda_{ypd(GAD)} * vProd_{yptd} - pFCost_{t} * vProd_{yptd} - \sum_{ygd} pInvC_{g} * \left(vNewGen_{ygd} \right) \\ - \sum_{ydd'} pInvC_{dd'} * \left(vNewLine_{ydd'} \right) \end{aligned} \quad (104)$$

$$A = \left\{ (y, p, t, d) \mid y \in Y, (p, rp) \in \Gamma_{rp,p}, t \in T, d \in D \right\}$$

Table XVII: Generation Expansion

		Generation Company	Generation Exp (MW)	Annual Inv Cost (M€)
GF	PC	C3, CCGT	560	16.80
	CO	C3, CCGT	545	16.36
BF	PC	C2, CCGT	360	
		C3, CCGT	57.5	13.10
	CO	C3, CCGT	350	10.52

Table XVIII contains the Total Costs of the System (TCS), Operational Costs (OC), System Demand (SD) and the Relative Operational Costs per TWh produced (ROC). Table XIX

		SW (M€)	PS (M€)	RPS [p.u]	TI (MW)	DSI (MWh/MW)
GF	**PC**	1282	294	0.22	1160	7.88
	CO	1405	394	0.28	945	9.27

BF	**PC**	1088	324	0.29	617	10.99
	CO	1113	379	0.34	550	15.95

contains Social Welfare (SW), Producer Surplus (PS), Relative Produce Surplus (RPS), Total Investment (TI) and Demand Supplied per MW of Investment (DSI), computed as the ratio between SD and TI, for each one of the scenarios and cases. At first glance, we obtain some counterintuitive results. For both GF and BF scenarios PC total costs are higher than CO total costs, however, as seen in Table XVIII this is mainly true because in the PC case more SD is met compared to CO. Therefore, if we compute the ROC, we obtain that ROC in PC is lower than in the CO case. This supports the hypothesis, mentioned above, that higher investment in PC leads to lower ROC while a lower investment in CO leads to higher ROC.

We can see in Table XIX, surprisingly, that CO welfare is higher than PC welfare. This suggests that, for sequential games, the absence of perfect competition in the market can be beneficial to society as a whole. In fact, similar results have been observed in [111]. Authors in [111] show that, when operation is anticipated by capacity expansion, social welfare results are case-dependent and therefore we can obtain cases with higher efficiency in Cournot competition than in perfect competition. Even though market power increases (seen as producer surplus increases) total welfare is still higher in the CO case.

For this purpose, we have computed the relative producer surplus (RPS) as the ratio between PS and welfare. As seen in Table XIX in both GF and BF cases RPS is greater in CO than in PC. This result indicates that more market power can actually be beneficial to society depending on the case at hand. This can be explained by the fact that the amount of demand supplied by one MW of investment (DSI) is greater in CO than in PC case, as seen the last column of Table XVIII. Somehow, the investment that is taken under CO is more efficient as it supplies more demand relatively speaking. This fact can also be explained by the network effects occurring in a non-arbitrage Cournot spatial model as seen in Figure 15. In such a case, flows can be inverted given that, as mentioned in [58], the elasticity at some nodes incentivizes generators to reduce prices, and with the absence of a marketer this leads to non-cost based price differences. Therefore, this may cause that reduced transmission capacity increases welfare in some cases.

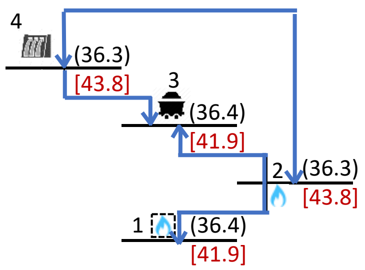
Additionally, the RPS for CO in BF scenario is greater than RPS for CO in GF scenario. This can be explained because the given network in BF is not optimal and not perfect, and therefore companies are capable of exercising a greater market power. Moreover, it is also true for the inverse case. The relative consumer surplus RCS=(1-RPS) in PC is greater than in CO case for both GF and BF scenarios. Additionally, RCS for PC case in GF scenario is greater compared to the PC case in BF scenario, in accordance to the fact the PC leads to an optimal setting and therefore consumer surplus is greater.

Table XVIII: Costs

		TSC (M€)	TIC (M€)	OC (M€)	SD (TWh)	SPD (GW)	ROC M€/TWh
GF	**PC**	210	17.2	148	9.15	1.88	16.19
	CO	191	17.1	144	8.77	1.95	16.49
BF	**PC**	187	13.9	143	8.99	1.54	16.00
	CO	172	10.9	146	8.79	1.24	16.66

Table XIX: Welfare

		SW (M€)	PS (M€)	RPS [p.u]	TI (MW)	DSI (MWh/MW)
GF	**PC**	1282	294	0.22	1160	7.88
	CO	1405	394	0.28	945	9.27
BF	**PC**	1088	324	0.29	617	10.99
	CO	1113	379	0.34	550	15.95



	PC		**CO**	
	% p.u.	RENT M€	% p.u.	RENT M€
4-2	0	0		
2-3	40	0.001	0	0
2-1	70	10	100	15
4-3	0	0	40	3

Figure 15: Flows Direction and Congestion BrownField

Moreover, In Figure 16 we can study how companies' market share varies in the different scenarios. We compute it as the relative production of each company over total production. In each scenario, the inner circle refers to the PC case while the outer circle refers to the OC case. On the one hand, in GF, the market share of each company under PC and CO are very close, strategic behavior does not defers from perfect competition. This can be explained because in the GF scenario, the leader TSO decides over most capacity and can lead to a closer competitive market under the CO case. On the other hand, the market share changes drastically from PC to OC under BF scenarios. This is due to the initial configuration of the network in BF. The fact that in the BF line (1-2) is already built (which otherwise would not be) makes company 2 and 3 to be more cost efficient. In addition, in the CO case it leads to an increase, of companies 2 and 3, of relative market power compared to company 4.

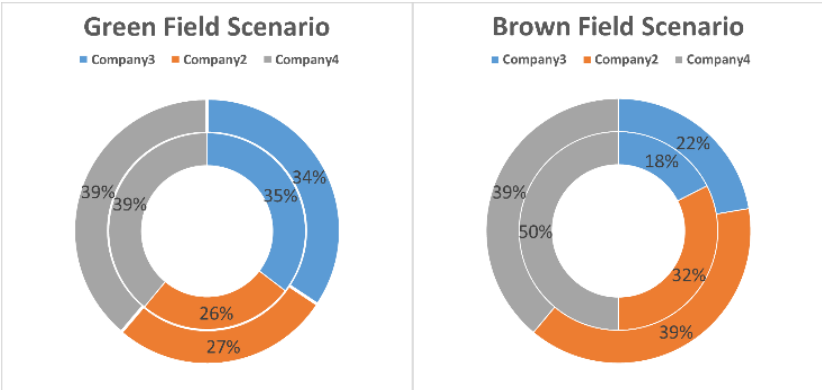


Figure 16: Market Share

In Figure 15 we show the directions of the power flow for the Brownfield case. In the black upper brackets and the lower red brackets, we present the average prices (€/MWh) per node for the PC and the CO case respectively. The arrows in Figure 15 represent the direction of the flows through the lines. This direction is the same during all hours, except for line (4-2) (which is only built in the PC case) where flows appear in both directions. In the CO case line (2-3) is never congested, (2-1) is always congested and (4-3) is congested 40% of the time of the year. For the PC case lines (4-2) and (4-3) are never congested while (2-3) and (2-1) are congested 4% and 75% of the time respectively. As we can see, in the PC case lines are less congested and average prices are closer. As expected in the PC case, flows on average go from low price nodes to high prices nodes. However, in the CO case the direction of power flows are inverse and go from high prices to low prices, a counterintuitive results already seen in [58]. As mentioned above, this can happen because the elasticity at some nodes incentivizes generators to reduce prices, and with the absence of a marketer, this leads to non-cost based price difference.

<u>Storage Results</u>

Finally, we analyze an additional scenario with storage investment. We take the same system configuration as in Figure 14, but we replace the CCGT candidate generator in node 1, with a Battery (B) belonging to company 4. We call this new scenario Storage Brown Field (SBF) in contrast to the previous Brown Field Scenario with CCGT candidates (now CBF). We consider a battery with 250MWh of installed capacity, 50 MW of maximum charge/discharge and investment cost of 400k€/MW. Table XX contains Invested Lines (IL), Transmission Capacity Investment (TCI), Invested Generation (IG), Storage (S), Generation Capacity Invested (GCI), Total Investment (TI) defined as TCI+GCI, System Demand (SD) and Demand Supplied per MW Installed (DSI). As we can see in Table XX DSI is higher for both PC and CO compared to CBF scenario. This means that the joint TEP and GEP investment in the storage case is more efficient than TEP and GEP in the base case. Additionally, DSI in CO is much higher than in PC, which suggests that, in this case, storage investments are more efficient in CO than in PC.

Table XX: SBF Capacity Expansion

	IL	TCI (MW)	IG & S	GCI (MW)	TI (MW)	SD (GWh)	PSD (GWh)	DSI (MWh/MW)	WF (M€)	RWF (M€)
PC	2-4	200	C2, B	36.4	236.4	7	1.37	29	813	116
CO	-	0	C2, B	37.7	0	4.5	0.87	119	742	164

Moreover, Figure 17 shows the usage of the battery (normalized by maximum capacity), we select the period of the year from h3600-h4200. As we can see, for the CO case the battery level is kept higher than PC case. The discharge cycles[28] are similar but in CO the battery reaches higher levels for both upper and lower bounds, this makes the percentage of energy produced by battery (over total production) in CO case 19% compared to a 13% on the PC case. Therefore, in CO the installed battery is used more than under PC. However, in CO prices are higher because COAL (with higher variable costs) is the new peaking unit, which replaces CCGT in PC. These results lead to a greater total welfare in PC compared to CO as seen in Table XX. Additionally, taking into account that the Demand Supplied by Investment (DSI) is much higher in CO than PC, again the Relative Welfare (RW) is greater in CO than PC.

[28] Please note that the battery cycles are daily because of our choice of representative periods as days. Therefore, as mentioned in [45] if the true period of the cycles (for a fully hourly model) are longer than 1 day, they can be misrepresented by the representative periods approach.

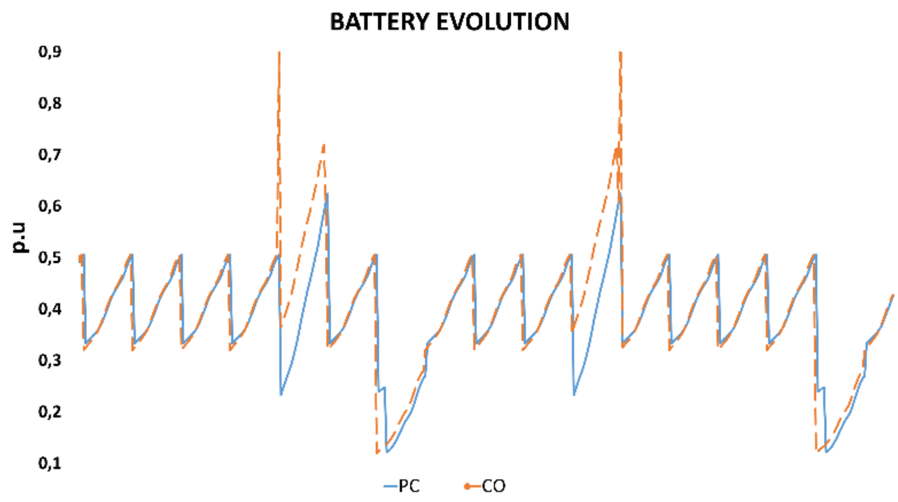


Figure 17: Battery Usage

Conclusions

In this paper, we develop an analytical framework to study the strategic interaction between a centralized transmission planner and decentralized GENCOs. As a novelty, we apply an enhanced representative-period framework that permits us to introduce both long-term and short-term operation constraints to study the yearly evolution of the energy stored. Additionally, we compare the investment and welfare results in a proactive transmission expansion framework where the TSO anticipates either perfect or Cournot competition in the market. We obtain some counterintuitive results where Cournot competition in bi-level models, under some circumstances, can be beneficial to society as a whole. We also see that a Greenfield planning leads to lower market power compared to a Brownfield planning. For future work, stochasticity can be introduced in order to model renewables accurately. Additionally, this can help to enrich the analysis of strategic competition between production and investment decisions. Finally, a linearized loss approximation or AC approach can be introduced to both to eliminate multiple solutions and to have more accurate dispatch results.

4.3 Transmission expansion planning under imperfect market competition: social planner versus merchant investor

Introduction

In modern electricity markets, centralized and regulated transmission system operators (TSOs) decide network expansion, by aiming to minimize total costs (or maximize welfare), while decentralized generation companies (GENCOs) decide their generation investment by maximizing their own profit. This market structure creates contradictory incentives between these two market participants and can lead to different outputs depending on who is considered as the leader in the market. We first introduce the existing regulatory approaches for transmission and generation expansion planning. Then, we present the relevant literature and finally, we state our research question and objectives.

Regulatory Approaches

Originally, power systems were planned by vertically integrated utilities (that owns the transmission and generation assets, see Figure 18) with a cost-minimization objective, in which Generation Expansion Planning (GEP), Transmission Expansion Planning (TEP) and operation decisions were simultaneously taken under the assumptions of inelastic demand, perfect information and in the absence of competition.

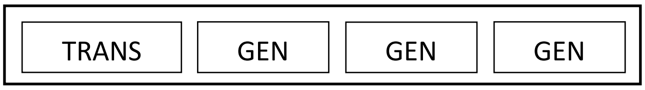


Figure 18: Cost-minimizing centralized approach

However, such a planning framework is highly questionable in modern markets. The generation business has been liberalized by allowing GENCOs to invest and operate freely, while transmission investment decisions are still regulated and operated by a centralized transmission company (TRANSCO). As seen in Figure 19 and Figure 20, this liberalized framework can be modeled considering two main regulatory approaches:

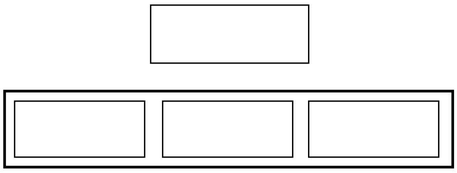


Figure 20: Proactive Approach

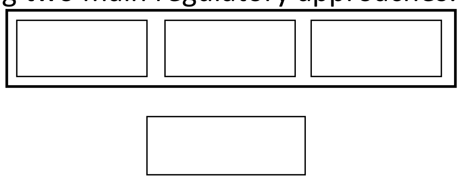


Figure 19: Reactive Approach

In the proactive approach, we consider that the TSO[29] is the leader in the market that takes its transmission investment decisions (TEP) by anticipating the generation investment (GEP) and operation decisions of GENCOs. In the reactive approach, the TSO is the follower that reacts to GENCOs decisions. Please note that a proactive approach with inelastic demand and perfect competition is equivalent to the previously presented cost-minimizing approach.

[29] We consider that the TRANSCO is in fact a regulated TSO.

Despite the theoretical optimality of the proactive approach [86],[112], most of the TSOs in the world follow a reactive approach [25]. Some countries [87] are applying regulations similar to the proactive approach (as originally proposed by [36]). For example, the US government approved a regulation that includes the concept of anticipative (proactive) transmission planning [95]. Similarly, the Chilean government approved a regulation that enforces the consideration of coordination between transmission and generation planning [96]. Lastly, in the current European context, ENTSOE plays the role of a centralized and regional coordinator that proposes future planning pathways [7], by anticipating how generation companies can react on a national scope.

As a consequence of the mentioned advantages, we decide to implement a proactive planning approach. It is important to note that, under this framework, GENCOs can potentially behave strategically in both generation expansion and operation. From now on, we will call this behavior the 'strategic market feedback'. This potential strategic behavior, on which we will focus, is particularly relevant nowadays given several features: i) construction times for transmission lines are consistently higher compared to construction times for generating units ii) high penetration of intermittent renewable technologies with decreasing capital costs iii) introduction of Battery Energy Storage Systems (BESS).

Although energy storage existed already in the form of pumped hydro, BESS (whose global deployment in 2018 has doubled that of 2017 [113]) present additional features: i) they help stabilize market prices [73]; ii) they can be sited anywhere in the network and can react more rapidly to the operational needs; iii) they are natural arbitragers of the market; and, iv) they can either be supplementary (replace the network) or complementary (reinforce transmission services) to the network [114], [23], [115], [116].

Finally, as a consequence of the complex deployment of energy systems, sometimes merchant transmission investors are essential to deploy certain types of projects (international tie-lines or interconnections for off-shore wind farms). Therefore, we also consider the case of an investor that takes its investment decision by trying to maximize its incomes, known as congestions rent.

Literature Review

Recently, there has been continuous research on power systems on what we call 'co-planning equilibrium models for generation and transmission expansion planning (GEPTEP) [72], [73], [85], [87], [90], [117], [118]. These models refer to the joint GEPTEP considering a decentralized market framework. In contrast to the GEPTEP co-optimization problem (centralized cost-minimizing approach), co-planning problems embrace a more general market structure which considers both sequential (e.g.; first TEP and then GEP) and strategic decisions (e.g.; Cournot competition). This type of structure leads to a hierarchical optimization problem that is complex to solve. For a detailed review of co-planning equilibrium problems please refer to [119].

Typically, GEPTEP co-planning models include three types of market agents, namely: GENCOs, the TSO and the Market Operator (MO). Accordingly, a three-level hierarchical structure is usually considered [88] [120]; some investment decisions GEP (or TEP) are decided in the upper level given some other TEP (or GEP) investment decisions in the middle level[30] and subject to the spot market (where GENCOs and the MO interact)[31] in the lower level. This three-level equilibrium structure implies solving a complex Equilibrium Problem with Equilibrium Constraints (EPEC) whose solution techniques are an active field of research [60]. Alternatively, instead of a three-level structure, we can consider a bi-level equilibrium that implies solving a Mathematical Problem with Equilibrium Constraints (MPEC). Following the proactive approach, we consider the TSO in the upper level (which is in charge of deciding TEP), and simultaneously GENCOs (GEP and operation) and MO in the lower level, as the structure depicted in Figure 20. In this paper, and following the approach of [75] and [76], we consider imperfect competition in the lower level (contrary to most works that consider perfect competition) with a conjectured price response framework (based on [111] which presents the single-level equivalent of a bi-level model using conjectural variations). For more details see Section 1.1.2.

As mentioned in the previous Section, BESS are becoming more and more important as they bring several advantages to the network. To our knowledge, only [82] and [73] have considered comprehensive storage co-planning models. On the one hand, authors in [82] develop a tri-level reactive model, they assume a merchant storage investor in the upper level, while transmission expansion and market operation are modeled in the middle and lower level respectively. On the other hand, authors in [73] model battery expansion in the lower level and choose a pessimistic TSO (with certain uniqueness properties) in the upper level. However, both [82] and [73] assume perfect competition in the market and disregard hydro storage. Additionally, authors in [74] consider a stochastic bi-level model with a merchant transmission investor in the upper level and both wind expansion and strategic operation in the lower level.

In this type of planning models, there is a common trade-off between a detailed representation of technical operating constraints and models tractability. In particular, it is difficult to jointly consider storage facilities that operate in different time horizons because the choice of time representation (i.e., load levels vs representative hours) would naturally facilitate the representation of one storage facility over the other (i.e., pump-hydro vs batteries). Consequently, authors in [75] and [76], apply a similar structure to the one proposed by [74], considering Cournot competition in the lower level, but they model both short- and long-term storage by applying the enhanced

[30] Depending if a proactive or reactive approach is considered

[31] Some models even consider a sequence between the market clearing and the operation

representative periods approach proposed by [45]. In the present paper, we extend our work in [75] in several forms: i) we incorporate different GENCOs ownership structures in the lower level ii) we develop a comprehensive policy analysis by considering distinctive network setups iii) we introduce a linearized merchant investor formulation and compare to a social planner as presented below.

Most of the articles discussed above assume that a regulated transmission planner is in charge of network expansion. However, merchant investors are sometimes essential carry out certain type of project, namely, international tie-lines or interconnections for off-shore wind farms. Articles [72]–[74] have addressed this topic in the literature; authors in [72] compare a merchant investor with a social planner by considering perfect competition in the lower level. Additionally, authors in [73] extend the work of [72], by modeling BESS in a zonal pricing scheme under a perfect competition environment. In contrast, authors in [74] model a transmission merchant investor subject to wind expansion and Cournot competition, disregarding storage operation and considering only a 3-node case. In summary, we propose a novel proactive model that considers both social and merchant transmission planners that anticipate the strategic behavior of GENCOs, that in turn, own a diversified portfolio including renewable and long and short-term storage technologies.

Policy Question and Contributions

Despite the fact that most of the electricity markets in the world are liberalized, transmission planners do not consider these kinds of interactions in the market and they continue planning TEP under a traditional cost-minimizing approach (assuming the results of a centralized GEP expansion). Thus, we raise the question of how much the ideal generation capacity investment, assumed by optimistic TSOs in a cost-minimizing approach, differs from reality (as a result of the strategic market interactions between GENCOs)? What is the cost of sub-optimal transmission expansion planning due to overly optimistic generation capacity expansion assumptions? How can we factor in strategic market feedback in an optimal transmission expansion plan? We propose a methodology that allows us to compute the welfare loss between a simple and overly optimistic cost minimization approach, instead of a more complex approach where a TSO foresees strategic market outcomes. In other words, we want to compare how the operation and investment decisions under perfect or Cournot competition can affect the transmission decisions and the overall social welfare.

Additionally we compare how different ownership structures in the market (owning more than one technology) influence the exercise of market power and how they affect overall welfare results. Finally, we also compare distinctive planning objectives for centralized planners and we compare them with a merchant transmission investor.

Our contributions are threefold: i) we carry out a comprehensive policy analysis in which we study the implications of disregarding market feedback (and having distinctive ownership structures) in transmission expansion planning under different systems set-ups; ii) apart from a social planner, we consider a merchant transmission investor who recovers its investment by maximizing congestions rents; iii) we are the first to comprehensively consider strategic investment in both batteries (short-term storage) and pumped-hydro (medium-term storage) in bi-level models.

Mathematical Formulation

In this Section we present the main structure of the corresponding models, we include the main constraints and main decision variables. Given that the main formulation was already presented in Section 69, we omit the detailed formulation here. However, in this Section we include the novel formulation of a merchant transmission investor, which is one of the contributions of this paper.

Benchmark: Cost Minimization Model (CMM)

Traditionally, capacity expansion has been planned from the point of view of a centralized vertically-integrated utility. In such a framework, depicted in Figure 21, the central planner decides *simultaneously* transmission and generation capacity expansion as well as the market operation by minimizing the total system cost. Additionally, the central planner assumes perfect competition and perfect information.

Single Level	Central planner Decides TEP, GEP, dispatch and power flows Minimizes Total Cost (investment +operation)

Figure 21: Cost Minimization Structure

It is important to note that, there is always a trade-off between how fine time granularity is considered and how detailed market operation is modeled. This disjunctive is especially important for the simultaneous representation of hydro and battery storage. In fact, most models consider either a load blocks (systems states) or representative periods. However, each of these options is more suitable for either of the storage technologies. In order to overcome this issue we consider an enhanced representative periods framework proposed by [45], which considers a representative-periods approach together with a transition matrix that gives count of how each representative period is connected to each other. From this framework, it is not only possible to model the battery storage with its intraday charging cycle, but also the hydro operation with its interday charging cycles by taking advantage of the links between representative periods. In this sense, a time window (more than a day, i.e week or month) is chosen to verify the hydro storage balance and follow the yearly evolution of the reservoir. Apart from this consideration, this model includes basic operating constraints.

The main constraints considered are:

i) Maximum and minimum power outputs for existing and new conventional generators, new investments are considered as continuous variables.
ii) Maximum and minimum power outputs for existing and new wind generators, considering them as non-dispatchable technologies.
iii) Maximum and minimum power outputs and consumption inputs for storage units. Considering both inter-day constraints for short-term technologies (BESS) and intra-day constraints for long-term storage technologies (hydro).
iv) Power flow constraints considering a linearized DC power flow for existing and new lines, we consider binary variables for network expansion.
v) Market clearing condition.

<u>Bi-level Problem: Proactive Model (PM)</u>

We consider a proactive approach in which the TSO plans the system, as the leader in the market, by anticipating both GEP and operation decisions.

1.1.1. Bi-level Structure

<table>
<tr><td>Upper Level</td><td colspan="3">TSO or Social Planner (decides TEP)</td></tr>
<tr><td rowspan="2">Lower Level</td><td>GENCOs
(decide GEP and operation)
Maximize Profits</td><td>SO
(decides power flow)
Maximizes
Congestion Rents</td><td>Consumers
(decide demand)
Maximize
Demand Utility</td></tr>
<tr><td colspan="3">Market Clearing Condition</td></tr>
</table>

Figure 22: Bi-level Model Structure

Let us explain the main differences between the CMM (Section 0) and the PM frameworks.

First, in the upper level, we consider two distinctive objectives for the social planner, namely, cost minimization and welfare maximization. Please note that the cost minimization objective considered here is the same as the one in the CMM framework. Please also note that a welfare maximization objective and a cost minimization only lead to the same results when there is inelastic demand, perfect competition and simultaneous decisions. Therefore, we compare the planning results of considering both planning objectives in an imperfect, elastic and sequential market model.

Second, in the lower level we consider three type players (each one with their own optimization problem), namely, GENCOs, the system operator (SO) and Consumers. The collection of these players' constraints is the same as that of the CMM framework. Finally, the *market clearing condition* couples every player's optimization problem, by ensuring that total supply is equal to the demand at each node. This constraint in the only one that differs from the CMM, given that in CMM the demand is a parameter (inelastic) while in the PM framework it is considered to be variable (elastic demand) see 1.1.2.

Mathematically speaking, Figure 22 shows a structure in which an optimization problem (upper level) is constrained by several optimization problems (lower level). Please note that such a structure cannot be solved directly as an optimization problem, therefore, we need to transform it into a single-level problem. First, we convert the set of optimization problems at the lower level into a set of constraints, by considering the equivalent KKT conditions. These conditions, which include some non-linear complementarity conditions, can be linearized by applying the well-known disjunctive constraints [101] with tight and meaningful big-Ms [100]. To sum up, this process leads to a single-level MIP problem where the upper level optimization problem is subject to a set of linearized equilibrium constraints. For details, please refer to Appendix.

1.1.2. Market Responsive Framework

Following the work of [71], we consider an affine relation between price and demand as shown in (105), i.e., demand is elastic, where *pDemand* represents the inelastic part of the demand and *pDslope* represents the slope of this function, which can be interpreted as how demand reacts to prices. Therefore, for a given node the demand would be given by (1).

$$vDemand_d = pDemand_d - pDslope_d * \lambda \ \forall d \tag{105}$$

We furthermore define a conjectural variation $\theta_g = \partial\lambda/\partial vProd_g$ that is assumed to be known for every GENCO *g.* This conjecture corresponds to each GENCO's belief on how much they can impact market prices by varying production $vProd_g$. If $\theta_g = 0$ this represents perfect competition (PC), and if $\theta_g = 1/pDSlope$ (inverse of the slope of the residual demand curve) it represents a Cournot oligopoly (CO). Any intermediate value of the conjecture allows us to model different degrees of competitive behavior.

Regret Computation: CMM vs PM

In order to compare the benchmark model and the bi-level problem, we compute what we refer to as *regret*. The regret represents the additional cost (or missing welfare) resulting from planning the system in a centralized traditional manner (CMM), where all decisions are considered to be simultaneous and perfectly competitive, compared to planning the system in a more realistic decentralized manner (PM) where TEP decisions are assumed to be taken prior to GEP decisions and considering market feedback given by GENCOs strategic behavior. Given that the CMM model is inelastic, while the PM is elastic, a specific methodology is needed to make these models comparable. This methodology is depicted in Figure 23:

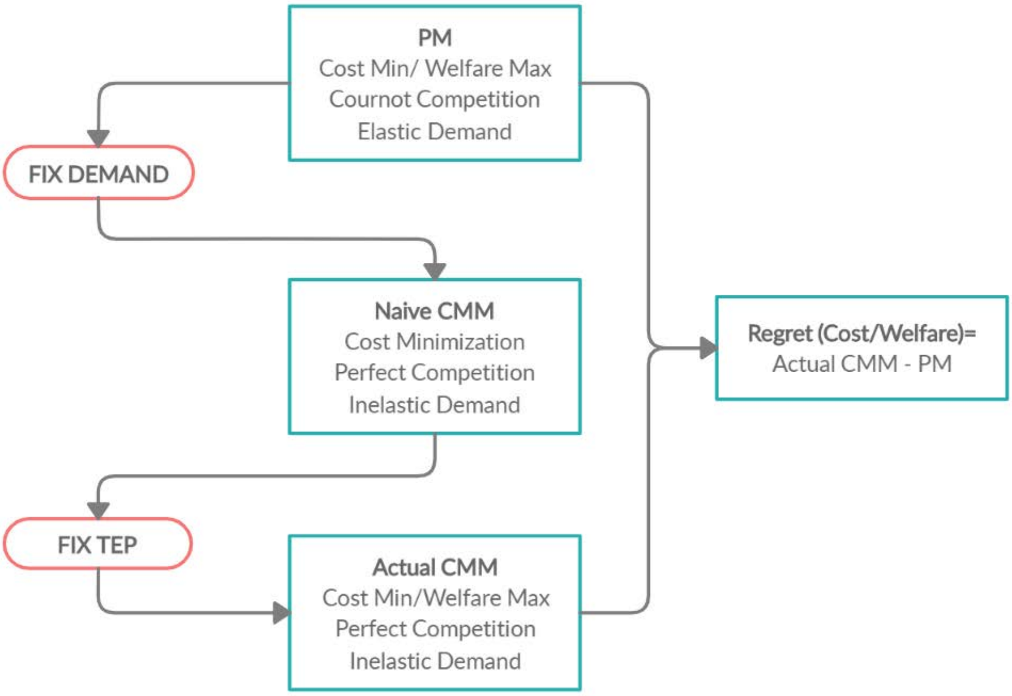


Figure 23: Regret Computation Methodology

i. We solve the *PM model* (considering Cournot competition in the lower level).
ii. For the exact same system demand obtained by the PM, we solve the inelastic CMM, which obtains some TEP and GEP investments (that might differ from the ones obtained by the PM). We refer to this model as the *Naïve CMM*; it is "naïve" because it does not reflect the strategic behavior of GENCOs. Therefore, the TEP and GEP obtained by the Naïve CMM might be erroneous given that they assume perfect competition, which is not always the case.
iii. We fix the TEP solution obtained by the naïve CMM, the one that would actually take place in a centralized planning system and see which would be the reaction of the actual strategic GENCOs. To this purpose, after fixing the TEP solution we re-run the PM model (which is equivalent to just solving the equilibrium problem described by the lower level of PM). This allows us to assess to what extent the

"wrong" TEP decision, obtained by the naïve CMM, is going to distort the resulting market equilibrium and GEP decisions made in imperfect markets. The solution of this third model allows us to compute the *Actual CMM* because it accounts for decision errors made by a cost minimization approach.

iv. Therefore, the regret of using a CMM approach is computed as total cost (or welfare) of the Actual CMM minus the total cost (or welfare) of the PM.

Bi-level Problem: Merchant TSO

Additionally to the social planner considered in Figure 22 (with a cost minimization and welfare maximization objective), we also consider a merchant transmission investor (contrary to a typically centralized regulated entity) that recovers its investment directly from the market operation. Such a model structure is depicted in Figure 23.

<table>
<tr><td>Upper Level</td><td colspan="3">Merchant TSO (decides TEP)
Maximizes Congestions Rents</td></tr>
<tr><td rowspan="2">Lower Level</td><td>GENCOs
(decide GEP and operation)
Maximize Profits</td><td>SO
(decides power flow)
Maximizes
Congestion Rents</td><td>Consumers
(decide demand)
Maximize
Demand Utility</td></tr>
<tr><td colspan="3">Market Clearing Condition</td></tr>
</table>

Figure 24: Bi-level Merchant TSO

We consider that those market incomes are derived from the network congestion rents, which are computed as the price difference between two connected nodes times the flow through the corresponding connecting line.

$$arg \underset{vFlows_{ypdd'}}{\text{Maximize}} \sum_{y,p,d} pW_{rp} * vFlows_{ypdd' \in LA} * (\lambda_{ypd'} - \lambda_{ypd}) - \sum_{ydd' \in LC} (Y - y + 1) * pInvC_{dd'} * \left(vNewLine_{ydd'} - vNewLine_{y-1,dd'}\right) \tag{106}$$

$$Subject\ to: Lower\ Level\ Problem$$

Please note that the lower problem is the same as the one of the social planner, which, as mentioned in 0, consists of the same constraints enumerated in 0 with addition of considering elastic demand. We consider that the only costs for the merchant investor are the investment costs. Let (106) represent the merchant investor's objective function. The first term of this objective function represents the congestion rents ($vFlows_{ypdd'}$ *

λ_{ypd} -$vFlows_{ypdd'} * \lambda_{ypd'}$) and corresponds to a non-linear, non-convex term, which can cause numerical difficulties when solving the problem. Therefore, we have decided to linearize this term in order to solve the resulting MPEC as a MILP just as the PM models at Section 1.1.1. Similar linearization techniques have been applied in bi-level models in [73], [102].

For illustration purposes we demonstrate how to linearize $vFlows_{ypdd'} * \lambda_{ypd'}$. We start by discretizing the variable $vFlows$, by applying a binary expansion as the one proposed in [102]. Equation (107) reconstructs $vFlows$ by starting from the lower bound and adding some slices until the upper bound of $vFlows$ is achieved.

$$vFlows_{ypdd'} = -pMaxFlows_{dd'} + \Delta Flows_{ypdd'} * \sum_{k} 2^k * vBinFlow_{ypdd'k} \quad (107)$$

Where $vBinFlow_{ypdd'k}$ is a binary variable and $\Delta Flows_{ypdd'}$ is the step magnitude in which we divide the variable $vFlows_{ypdd'}$, which is given by (108)

$$\Delta Flows_{ypdd'} = \left|-pMaxFlows_{ypdd'} - pMaxFlows_{ypdd'}\right|/2^K \quad (108)$$

Let us define the binary expansion of $vFlows_{ypdd'} * \lambda_{ypd'}$ in equation (109).

$$vFlows_{ypdd'} * \lambda_{ypd'} = -pMaxFlows_{dd'} * \lambda_{ypd'} + \Delta Flows_{ypdd'} * \sum_{k} 2^k * vBinFlow_{ypdd'k} * \lambda_{ypd'}. \quad (109)$$

Given that the nonlinear term $vBinFlow_{ypdd'k} * \lambda_{ypd' \in (GAD)}$ is the product of a binary variable and a continuous variable, we can linearize it by renaming the product $vF\lambda_{ypdd'k} = vBinFlow_{ypdd'k} * \lambda_{ypd'}$ and adding the two following equivalent equations:

$$0 \leq \lambda_{ypd' \in (GAD)} - vF\lambda_{ypdd'k} \leq \overline{\lambda} * (1 - vBinFlow_{ypdd'k}) \quad (110)$$

$$0 \leq vF\lambda_{ypdd'k} \leq \overline{\lambda} * (vBinFlow_{ypdd'k}) \quad (111)$$

Please note that we assume that prices are non-negative and therefore $\underline{\lambda}$ is zero.

Thus, we re-formulate the complete problem as follows:

$$\underset{vF\lambda_{ypdd'}}{\arg\text{Maximize}} \sum_{y,p,d} vF\lambda_{ypdd'} - vF\lambda_{ypd'} - \sum_{ydd'} (Y - y + 1) * pInvC_{dd'} * \left(vNewLine_{ydd'}\right) \tag{112}$$

$$Subject\ to: Equations\ \ (107) - (111)\ and\ Lower\ Level\ Problem$$

It is important to note that -as with every linearization technique- the result depends on the steps considered for the discretization. Therefore, the bigger k, the smaller is the step size, and hence, the closer the solution would be to the global optimum.

Case study

In order to test the properties of the proposed model we consider two case studies, an illustrative 3-node case, where we study in detail the investment and operation results and a modified 24-IEEE test case where we run a sensitivity analysis to generalize some policy implications.

Illustrative 3-Node Case

We start out by considering a simple three-node example with: one existing conventional generator (CCGT) located at Node_3; one candidate wind generator located at Node_1; and, one candidate Battery Energy Storage System (BEES) located at Node_2. We consider that each generation unit belongs to a different GENCO. Additionally, we study a green-field approach where there is no existing transmission infrastructure.

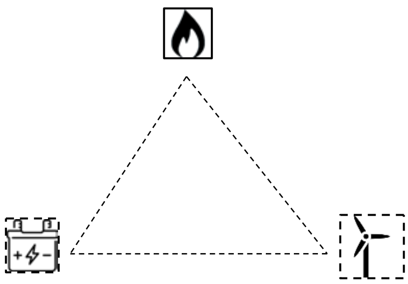


Figure 25: 3-Node System Characteristics

In Figure 25, dotted lines represent candidate elements, either generation units or transmission lines, while continuous lines represent existing elements. We consider a single representative day for a single target year.

Table XXI: 3-Node System line characteristics

From Node	To Node	Reactance [p.u]	Life Time (years)	Total Investment Cost (M€)	Annual Investment Cost (M€)	Capacity (MW)
1	2	0,06	40	2	0,125	20
2	3	0,05	40	2	0,125	20
1	3	0,03	40	2	0,125	20

Table XXII: 3-Node System GENCOs characteristics

	Node	Status	Life Time (years)	Total Capital Cost k€/MW	Annual Capital Cost k€/MW	Variable Cost €/MWh	Maximum Power Capacity MW
CCGT	3	existing			-	50	55
Wind	1	candidate	25	1000	85,80	0	26*
BESS	2	candidate	15	500	54,89	0	10*

Table XXI shows the technical characteristics of the transmission lines. We consider three candidate lines of 20 MW and 100 km with a total capital cost of 1000€/MW·km and a 5,5% discount rate which leads to the annual cost presented in Table XXI. Additionally, Table XXII shows the capital [121] and variable cost of GENCOs as well as their location and technical characteristics. Please note that the BESS has a 4-hour charge/discharge duration which implies a storage typical capacity of 40 MWh. In order to compute annual capital costs for GENCOs we consider a 7% discount rate [122].

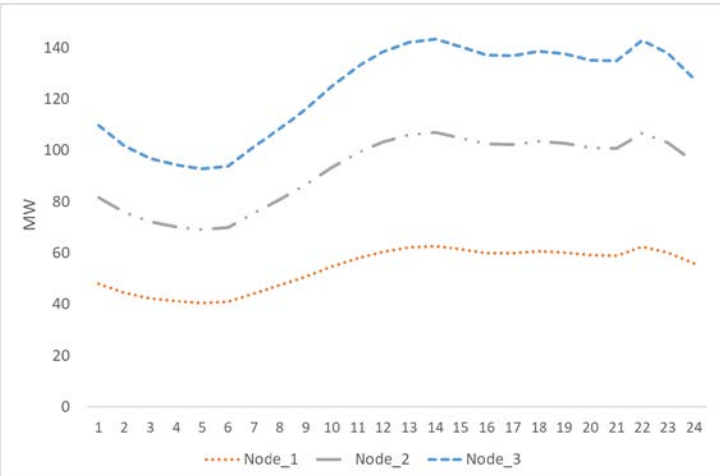


Figure 26: Hourly Demand Intercept

Figure 26 shows the hourly demand intercept at the 3 different nodes; additionally, for Node_2 and Node_3 we consider a constant demand slope (β) of 1,6 €/MWh^2 and for

Node_1 a slope of 2.5 €/MWh^2. These values are aligned with what is usually found in the literature [36], [74]. Finally, for this 3-Node case, we study two main ownership structures i) single ownership structure (SG), where each GENCO can own only one type of technology and ii) mixed ownership structure (MX) where we allow generators to own more than one type of technology in a single node.

Results: Single Ownership structure (SG)

In this Section we study capacity expansion planning considering a PM model with a *welfare-maximizing* social planner that anticipates different strategic market behavior, namely: Perfect Competition (PC), Cournot Oligopoly (CO), and Intermediate Competition (IC). The corresponding conjectural variations, defined in 1.1.2, appear in Table XXIII. Additionally, we consider a SG ownership structure where every GENCO can only own a single technology at each node.

Table XXIII: Conjectural variations for each degree of competition.

PC	IC	CO
0	$(1/\beta)/2$	$1/\beta$

Table XXIV: Economic results for the PM planning with distinctive market structures

		Units	PC	IC	CO
TEP		Lines	1-2/1-3/2-3	1-2/1-3/2-3	1-3/2-3
		MW	60,00	60,00	40,00
GEP					
	BESS	MW	15,41	11,13	3,28
		MWh	61,64	44,50	13,14
	Wind	MW	91,27	52,27	33,23
Total GEP		MW	106,68	63,39	36,52
Demand		TWh	6,94	5,38	4,31
Total Cost		M€	23,66	23,53	21,17
Relative Cost		M€/TWh	3,41	4,37	4,92
Total PS		M€	34,29	51,52	50,61
Total CS		M€	51,43	28,56	21,26
Total SW		M€	85,72	80,07	71,87

Investment Results

Table XXIV shows the economic results of planning the system under perfect, intermediate and Cournot competition. In the PC case the social planer decides to build all three candidate lines; this implies that, compared to the CO case, less congestions appear in the transmission lines (see Figure 27). In contrast, in the CO case only two lines are built and therefore less total generation is built because there is less transmission capacity to transport the excess of the wind (which cannot be used by the battery). Additionally, in the IC case all lines are built and therefore the energy excess from wind can be directly profited by storage, resulting in BESS investments more similar to the PC case.

As seen in Table XXIV the aforementioned investment plans lead to satisfying a total demand 38% lower in the CO case compared to the PC case. However, the total cost of the system in the PC case rises up to 23,66 M€, which is higher than the 21,17 M€ of the CO case. At first sight, this might seem counterintuitive; however, the relative cost (cost per unit of demand supplied) is lower in the PC case[32]. In contrast, the PC case naturally reaches the maximum social welfare which, in turn, is 19% higher than the CO case. As we can see, the decrease in the social welfare under de CO case is lower than the decrease in the total demand supplied, this happens because the proportion between the producer and consumer surplus is interchanged (evidencing a higher economic inefficiency than what is directly seen from the welfare loss). Please note that, in the Cournot case, the social planner avoids building a third line, which otherwise would have led to a worse-off situation. Let us analyze this in detail in Section 0. Finally, in terms of total demand, cost and welfare, the IC case is indeed intermediate between the perfect competition and Cournot oligopoly. However, even though the IC investments seem closer to PC case, the actual operation results are closer to the Cournot case, leading to a hidden welfare loss not reflected by the total social welfare.

Operation Results

The behavior described in Section 0 can be better understood by analyzing how production, flows and prices evolve within the representative day; as shown in Figure 27 and Figure 28. First, let us take a look at the PC case. Figure 27 shows the expected utilization of transmission lines, and therefore when transmission lines are congested (as indicated by areas S1- S4 depicted in Figure 27) distinctive nodal prices arise (see corresponding S1-S4 areas in Figure 28). Second, please note that there is not a single period at which prices directly reflect units' marginal cost. As seen in Figure 29, prices at Node_3 are always greater than 50 €/MWh, because at every hour the capacity of the CCGT_3 unit is at its maximum (as a consequence of a static greenfield planning model), and therefore prices reflect the consumers demand response. This means that the energy that consumers are willing to demand at a price of 50 €/MWh exceeds the available capacity of generators, and therefore consumers are willing to pay a price higher than 50 €/MWh.

[32] Please keep in mind that, considering a social welfare maximization in the PM model (by incorporating the consumers' preferences via the utility of demand) is not the same as minimizing total costs.

This can be appreciated in Figure 29, where *non-consumed energy*[33] is illustrated. Please note that this concept refers to actual demand consumers renounce given the resulting price in the market. This non-consumed energy is computed as the actual energy consumed minus the demand intercept at each hour, relative to this demand intercept (this ratio is 0 when prices are 0 and it is 1 when prices are at its maximum).

[33] Please note that the non-consumed energy concept is different from the non-served energy concept that is applied to inelastic models when consumers have an infinite (or very high) willingness to pay for energy.

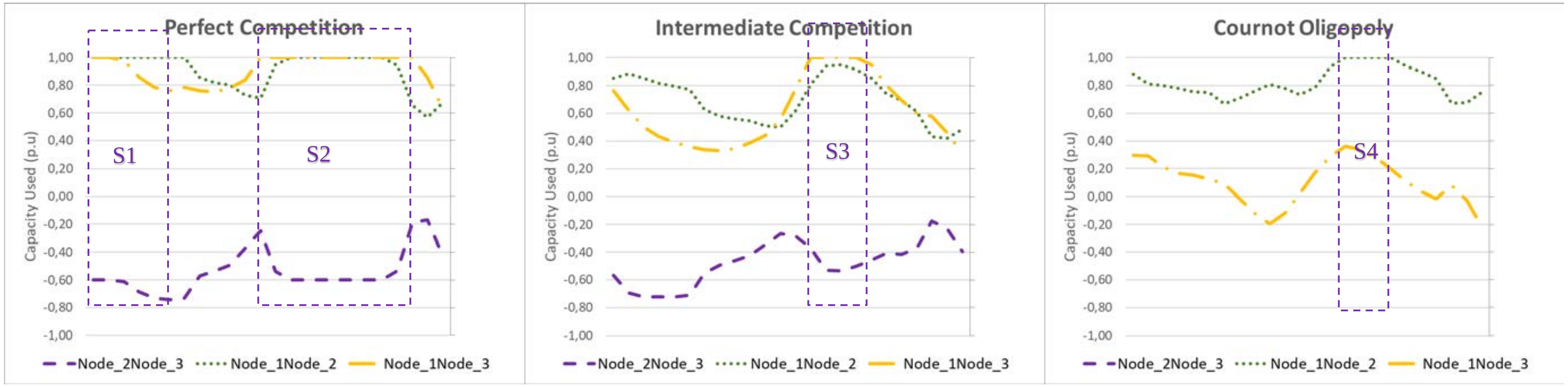


Figure 27: Flows through lines[34]

[34] Please note that a negative capacity usage means that the flows go in the contrary direction of the lines.

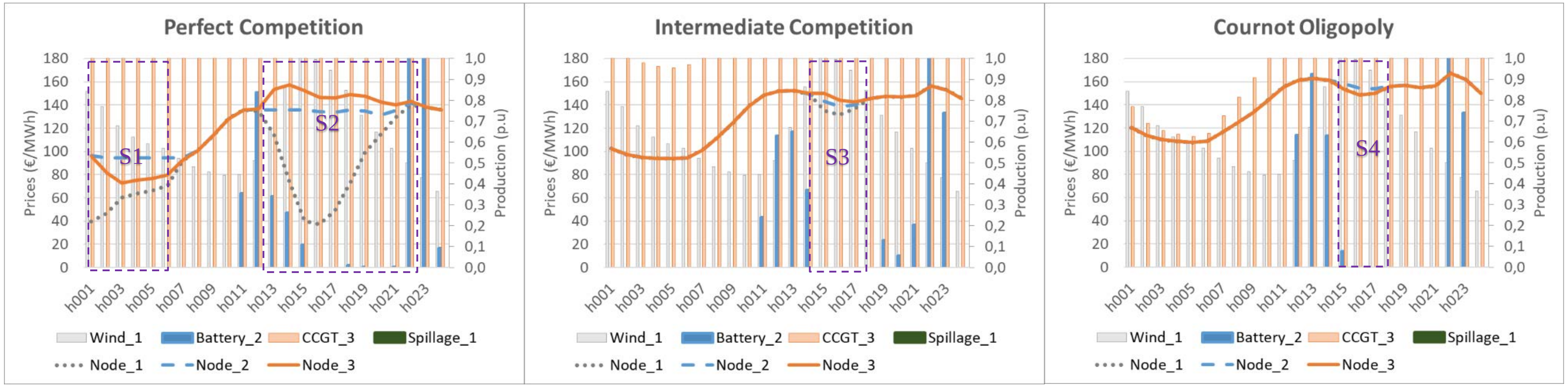


Figure 28: Prices (represented by lines) and Production (represented by bars)

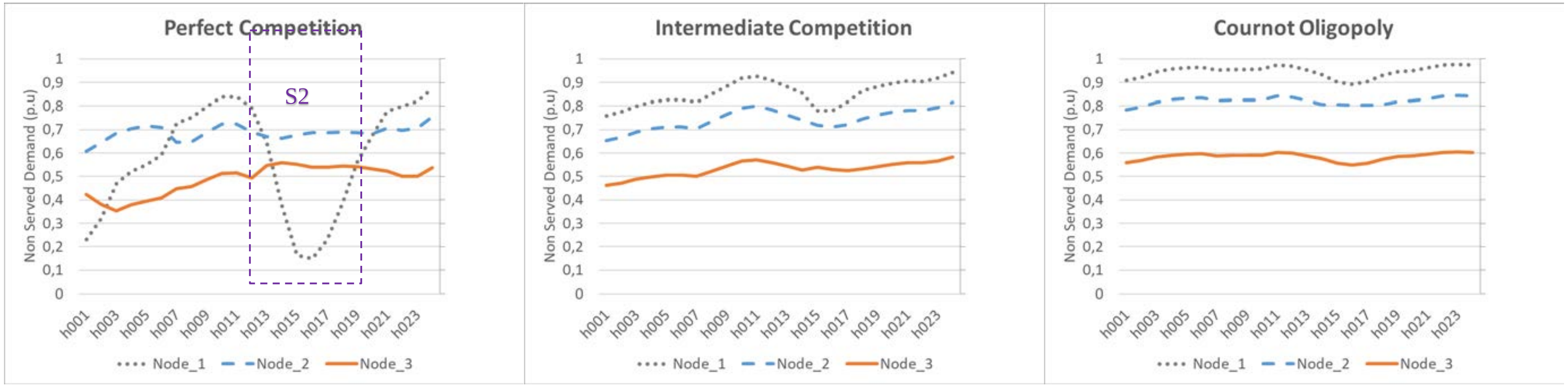


Figure 29: Hourly non-consumed energy per Node

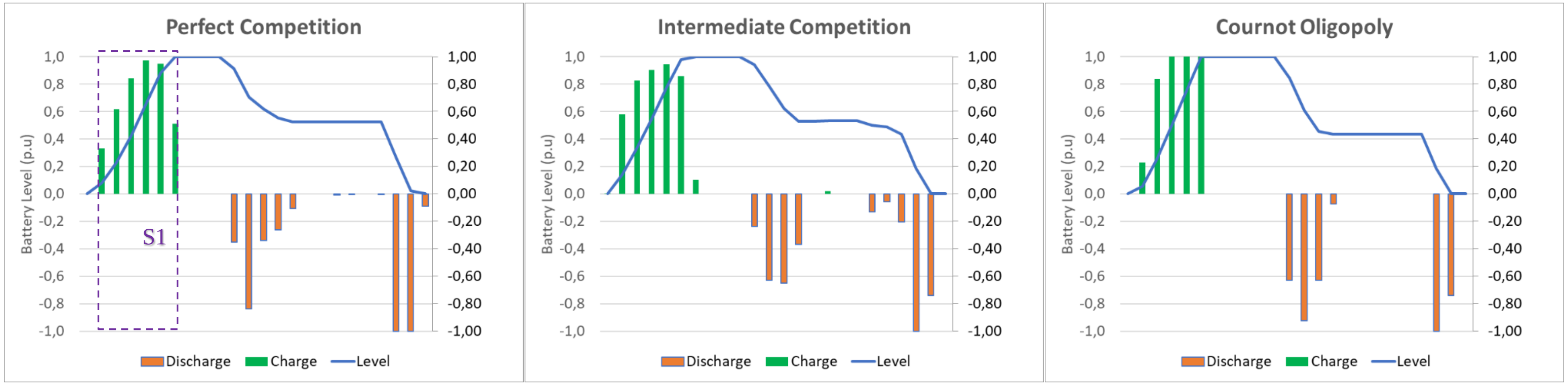


Figure 30: Battery Charge and Discharge (bars) and Battery Level (lines)

In this case when there is high “*non-consumed energy*” prices are high and when there is low *non-consumed energy* prices are low. In fact, price variations in Figure 28 (at hours of distinctive nodal prices) follow exactly the shape of the *non-consumed energy* at each node in Figure 29. Please keep in mind that this happens in the PC case only because generators are at their maximum capacity.

Finally, let us note some features of the battery operation. First, as shown in Figure 28, in the PC case, the battery produces at its maximum during peak hours when prices are higher, which is, in fact, the efficient way in which batteries operate (energy arbitrage). In other words, they charge energy in the low price hours, as seen Figure 30, represented by area S1, and discharge it in the high price hours. Please note that a consequence of the intertemporal arbitrage is price stabilization (because any intertemporal price difference, with idle storage capacity, is an opportunity for price arbitrage), which in this case can be appreciated when there are congestions in the network and nodal prices are isolated, as seen at Node_2 in depicted areas S1 and S2 in Figure 28.

In the CO case nodal prices[35] almost always converge because there is only a short congestion in line 1→2, as seen in area S4. However, in this case, the prices are higher than the PC case given that some generation is withheld, therefore prices contain a mark-up resulting from the elasticity of demand, even when generators have *idle capacity*. The operating results of the IC case are closer to the CO case, as seen from Figure 27 and Figure 28. Finally, from this operation and pricing analysis it is important to note that the IC and CO cases present a higher price convergence, which implies lower congestions, but actually leads to higher prices on average. Therefore, for this case, nodal price convergence might not be an appropriate a-posteriori criterion to evaluate market efficiency[36].

Regret of disregarding market feedback

In the previous Sections we considered a proactive model (PM) where a social planner aimed to maximize social welfare by anticipating different market structures in the lower level. In this Section we compute the regret, as introduced in 0, of planning the system in a centralized manner instead of planning with a PM model where the social planner anticipates the strategic market feedback i.e., Cournot competition in the lower level. Therefore, we compare the results of the CO model (in Section 0) now called PM_CO, with the Naïve and Actual CMM.

[35] When the oligopolistic competition is considered, pricing results might highly differ depending on the type of transmission price modeling, for more details see [62]

[36] In fact, in this case high-prices and price convergence reflect a system planning under imperfect competition

As seen in the previous Section, PM_CO invests in lines 1→2 and 1→3 which leads to a total welfare of 71,87 M€ with a supplied demand of 4,31 TWh. Given this exact same demand, imagine we have a Naïve CM planner that designs the system disregarding the strategic market feedback. In such a case the centralized planner based on the Naïve CMM would build lines 1→2 and 2→3 with the expectation that GENCOs would build and operate the most competitive generation capacity (please note that if the Naïve case happened it would actually lead to a higher welfare compared to PM_CO).

Table XXV: PM vs Cost Minimization

		Units	PM_CO	Naïve CM	Actual CMM
		Lines	1-2/1-3	1-2/2-3	1-2/2-3
Total TEP		MW	40,00	40,00	40,00
	BESS	MW	3,28	24,93	3,52
		MWh	13,14	99,70	14,08
	Wind	MW	33,23	24,54	31,48
Total GEP		MW	36,52	49,46	35,00
Demand		TWh	4,31	4,31	4,25
Total Cost		M€	21,17	36,61	36,22
Relative Cost		M€/TWh	4,92	8,50	8,53
Total PS		M€	50,56	15,33	50,03
Total CS		M€	21,31	56,87	21,29
Total SW		M€	71,87	72,19	71,33
Abs Regret		M€			0,55
% Regret					0,8

However, markets are not perfect and usually we can find an oligopoly in the production, therefore, we evaluate which are the actual results of the strategic market given the TEP decided by the Naïve CMM. We call this result the Actual CMM which leads to a total welfare of 71,33 M€ which is 0,55 M€ lower compared to the PM_CO.

This result is explained as follows: at the PM_CO the energy goes from Node_2 to Node_1 and the energy comes and goes between Node_1 to Node_3, which means the average net energy flows from Node_1 to Node_3 and to Node_2 (as seen in Figure 27). Now, given that at the Actual CMM line 2→3 is built instead of 1→3, the congestions increase, and less wind energy can be evacuated from Node_1 to supply demand at Node_3 trough Node_2. This leads to a lower wind investment, but a slightly larger BESS investment to store also some of the energy coming from Node_3. This shows that building line 2 → 3 instead of 1→3 leads to a 0,8% reduction in the total SW. Please note that either of these results leads to a better-off situation than actually building all possible lines. These findings are contrary to those of [74], where it was suggested that, in the CO case, the social planner would build as much lines as possible (when no storage is considered) to diminish GENCOs market power. We show here that, in the presence of storage units (and depending on demand elasticity), it can be the case that building more lines leads to a lower social welfare.

Results: Mixed Ownership Structure (MX)

In this Section we want to investigate what are the welfare effects of considering GENCOs with a multi-technology portfolio. For this purpose, we analyze two cases additional to the Single Ownership (SG) case (base case from Section 0). i) We consider that apart from wind generation, GENCO1 can invest in BESS[37], and we call this the Mixed Ownership BESS case (MB). ii) On top of i) let us consider that GENCO2 invests in hydro[38] instead of BESS and we call it the Mixed Ownership Hydro case (MH). Please find a summary of these cases in Table XXVI.

Table XXVI: Battery of cases

	SG	MB	MH
GENCO1	Wind_1	Wind_1	Wind_1
		BEES_1	BEES_1
GENCO2	BESS_2	BESS_2	Hydro_2
GENCO3	CCGT_3	CCGT_3	CCGT_3

Additionally, apart from considering distinctive ownership structures we analyze the possible planning differences of planning the system as a social planner vs a merchant investor. This comparison would allow us to understand how inefficient a merchant investor can be (compared to the social planner solution), and would allow policy makers make the right considerations when accepting this kind of investors for isolated or international connections.

[37] With the same technical characteristics as BESS at Node_2 see Table XXII
[38] With a capital cost of 140 M€/MW, a 0,80 roundtrip efficiency and a weekly (168h) of typical storage per MW installed.

Social Planner

Table XXVII: Economic results mixed ownership structure

		Mixed Battery (MB)		Mixed Hydro (MH)	
	Units	PC	CO	PC	CO
TEP	Lines	1-2/1-3/2-3	1-2/1-3	1-2/2-3	1-3
	MW	60,00	40,00	40,00	20,00
GEP					
BESS_2	MW	10,69	1,62	0,00	0,00
	MWh	42,77	6,47	0,00	0,00
HYDRO_2	MW	0,00	0,00	12,11	10,96
	MWh	0,00	0,00	2034,5	1841,28
BESS_1	MW	24,02	10,63	27,80	7,93
	MWh	96,08	42,50	111,18	31,72
Wind_1	MW	100,63	33,06	94,45	27,04
Total GEP	MW	138,85	48,97	159,62	75,57
Demand	TWh	7,28	4,32	8,87	5,76
Total Cost	M€	23,68	21,36	23,70	20,45
Total PS	M€	35,07	50,89	45,45	67,84
Total CS	M€	53,28	21,60	66,59	31,65
Total SW	M€	88,35	72,491	112,04	99,49

As shown in Table XXVII, and in accordance with the results in Section 0, transmission expansion and generation expansion are higher under a perfect competition than under Cournot oligopoly. Unsurprisingly, these investments lead to a higher welfare in the PC case for every ownership structure. However, let us study in detail how consumer surplus (CS) and producer surplus (PS) share vary for every case. Figure 31 shows the welfare distribution for each ownership structure, details of the Mixed Ownership are shown in Table XXVII while details of Single Ownership is shown in Table XXIV Section 0.

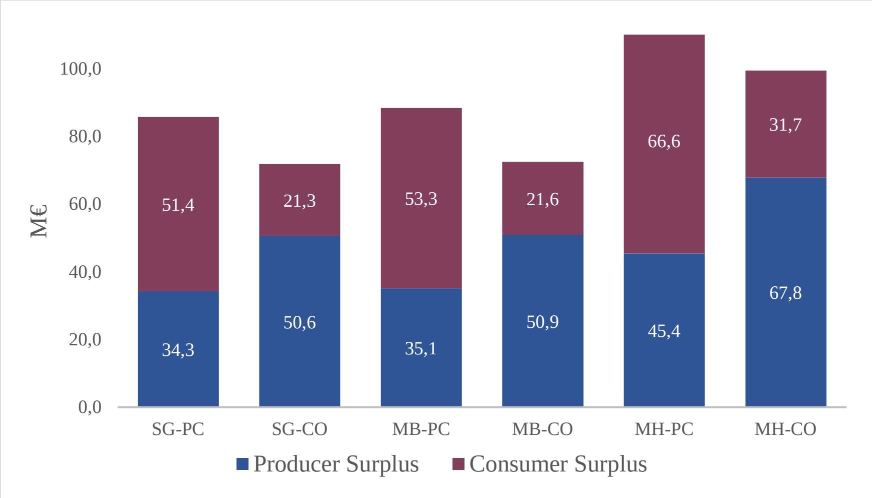


Figure 31: Welfare Distribution

First, we can see a consistency in the welfare distribution among all PC cases and among the CO cases respectively. In PC cases, 60% of welfare corresponds to CS and 40% to the PS, while in the CO case this share is inverted, and lies around the 35% for CS and 65% for PS. Please note that the PS and CS share depend both on the demand elasticity and the degree of competition. However, the PS share is always higher in the CO case compared to the PC case, as a result of the exercise of market power. Therefore, let us define the ratio PS/CS as an additional efficiency measure, whose lowest value would indicate a better-off situation, given that we keep the demand slope fix along the different cases.

Table XXVIII: PS/CS ratio each Cournot oligopoly case

	SO_CO	MB_CO	MH_CO
PS/CS	2,38	2,35	2,1

Table XXVIII shows that SG_CO is the most inefficient scenario. Even though in the MB_CO case GENCO 1 increases its profits, as seen in Figure 32, total demand supplied increases more than proportionally and the PS/CS ratio is actually lower. Please also note that at the hydro case (MH) the highest welfare is achieved, for both PC and CO cases (Table XXVII). Please note that the pumped hydro storage includes some natural inflows that the battery storage does not, and therefore, it represents some extra available power which increases total welfare. Additionally, the PS/CS ratio is lower in the MB case because the additional available hydro energy diminishes the amount of energy that GENCO2 can export, and in overall decreases GENCOs market power. This is also reflected in Figure 32, by the decrease of profits of GENCO1 from case MB_CO to MH_CO, while profits of GENCO2 increase, reflecting a higher competition among

GENCOs. Therefore, in this case study, a diversified generation portfolio seems to increase competition and results in more efficient planning and operation management.

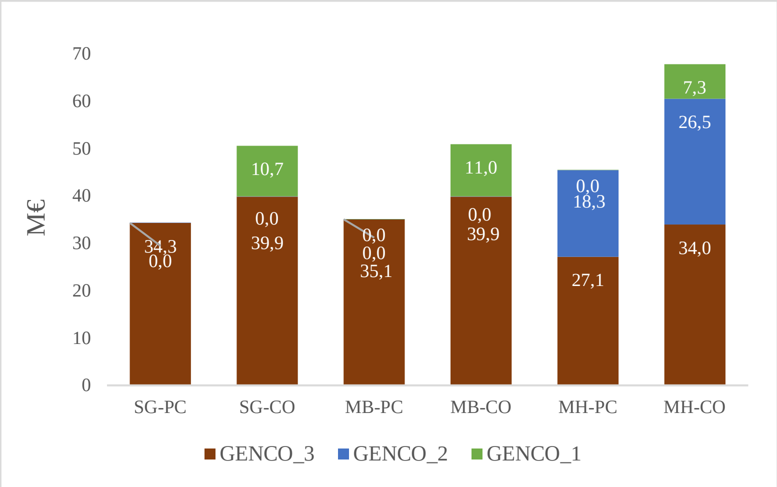


Figure 32: GENCOs profit distribution among different ownership structures

Merchant TSO

Finally, we analyze the economic results of a merchant transmission investor. As formulated in Section 0, we now consider a merchant agent at the upper level, that aims at maximizing its own profit. This type of regulation is not usually applied to a complete system but exists for specific project. For instance, merchant investment is applied for interconnections in Europe [123] and has been expanding in the US, in fact in 2018 the FERC extended the authorization for off-shore wind farms connections by allowing this type of investments, only if the merchant transmission company assumes all market risk [124].

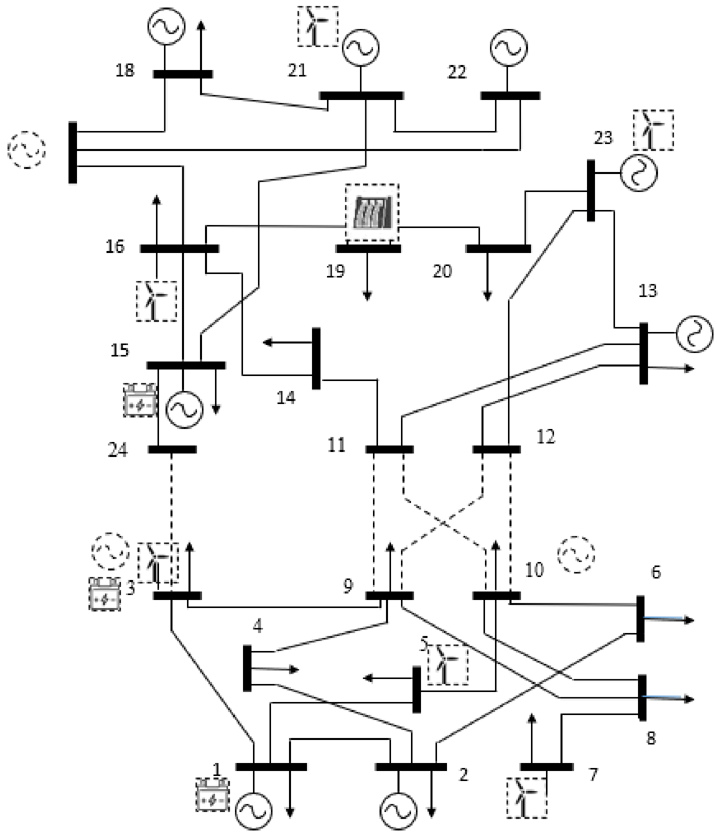
We apply this framework to the MH case from Section 0. As seen in Table XXIX, some interesting results appear when considering a merchant investor. In the PC case, having a merchant investor instead of a social planner leads to a welfare of 110,09 M€, which is 0,52% lower compared to the social welfare achieved by the social planner (see Table XXVII). It is interesting to note that both planners would invest in two lines, but in a different combination. A social planner would invest in lines 1→2 and 1→3 while merchant investor would invest in lines 1→2 and 2→3. In spite of the lower generation investment of the merchant case, there would be a higher congestion for generation at Node_3 trying to evacuate to Node_2. In contrast, in the CO case, the merchant transmission would invest in line 1→2, which would maximize congestions rents compared lines 1→3 built by social planner. This would lead to a 2,2% lower welfare compared to a social planner.

Table XXIX: Economic results of a merchant transmission investor

		Mixed Hydro (MH)	
	Units	PC	CO
TEP	Lines	1-2/2-3	1-2
	MW	40,00	20,00
GEP			
BESS_2	MW	0,00	0,00
	MWh	0,00	0,00
HYDRO_2	MW	14,69	10,98
	MWh	58,78	43,94
BESS_1	MW	17,22	7,98
	TWh	68,87	31,92
Wind_1	M€	71,22	27,72
Total GEP		127,64	75,86
Demand		7,99	5,78
Total Cost	M€	23,70	20,77
Total PS	M€	53,22	69,34
Total CS	M€	56,87	32,43
Total SW	M€	110,09	97,32

IEEE-24 bus test case

In order to test this model we consider an IEEE-24 modified system as the one considered in [114].



As seen in Figure 33, this system is made up of 24 buses, 33 existing lines, and 12 existing conventional generators. Continuous lines represent existing elements and dotted lines represent candidate lines. We consider 3 candidate conventional generators at nodes 3, 10, and 19, as well as 6 wind candidate generators at buses 3, 5, 7, 16, 21, 23.

Additionally, we consider 4 candidate BESS at nodes 1, 3, 15 and 1 hydro candidate at node 19. We consider 4 representative days (h3697-h3720, h8425-8848, h5305-h5328 and h1897-h1920). As seen in Figure 34, we consider different profiles for the wind candidate generators located in the south (nodes 3, 5, 7) and those located in the north (nodes 16, 21, 23). Additionally, we consider a yearly hydro inflow shown in Figure 35, and a 168h window (as defined in 0) for the inter-day storage constraints. We consider the same capital costs as in the 3-node case and a cost of 1300 k€/MW for conventional generators considering 30 years life-time and a 7% discount rate (equivalent to 104 M€/MW annually). Finally, we consider a transmission capacity of 50MW for each of the transmission lines (existing and candidates) of the system and a demand slope of 0,55 €/MWh^2.

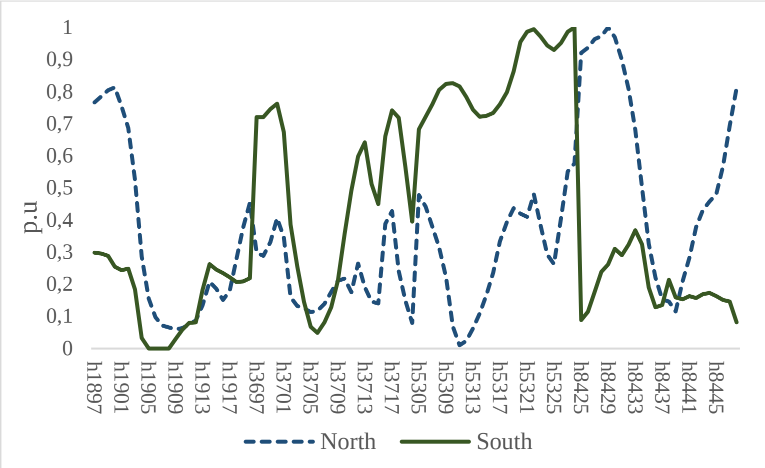


Figure 34: Wind Profiles

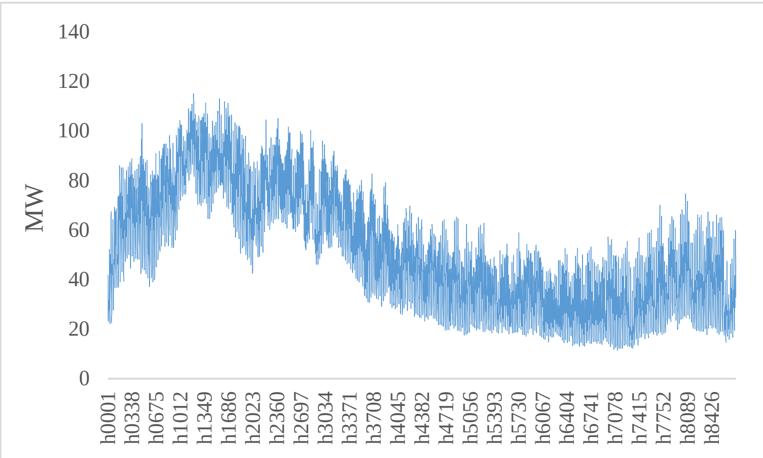


Figure 35: Yearly hydro inflows

Merchant TSO vs Social Planner

In this Section we evaluate the 24-Bus case. First, we compare the results of planning the system considering different planners and objective functions. Additional to the previous Section, we include a social planner with a cost-minimization objective. Please note that in this subSection, every model considers elastic demand.

Table XXX shows the economic results of planning the system considering distinctive objective functions for the social planner (maximizing welfare or minimizing cost) and the merchant investor (maximizing congestion rents). We compare the economic efficiency of such regulatory schemes by comparing total welfare at each case.

Let us point out that the welfare-maximizing and cost-minimizing objectives only lead to the same results when there are inelastic demand and perfect competition in the market. However, here we compare what are the planning results of a social planner with either a cost-minimizing or welfare-maximizing objective[39]. It is evident that the social planner with a welfare-maximizing objective achieves the highest social welfare, however it is interesting to note that, in the PC case, considering a cost-minimization objective for the social planner leads to the same sub-optimal equilibrium than the merchant investor who aims to maximize, its own profits. In the CO case, in fact, the merchant investor decisions lead to the worse-off situation overall. These results are case dependent, but they suggest that a social planner that minimizes cost in a market with elastic demand can lead to the same sub-optimal results as a merchant investor that maximizes congestion rents.

Table XXX: Economics Results 24-Node Case

		Perfect Competition (PC)			Cournot Oligopoly (CO)		
		Max Welfare	Min Cost	Max Rent	Max Welfare	Min Cost	Max Rent
TEP	**MW**	200	200	100	100	100	100
GEP	**MW**	1484,25	1481,77	1481,77	1016,07	1012,37	1012,37
Demand	**TWh**	7,20	7,42	7,42	2,53	2,50	2,71
Total Cost	**M€**	490,43	475,34	475,34	319,22	312,43	316,23
Relative Cost	**M€/TWh**	68,08	64,09	64,09	126,04	124,97	116,78
Cong. Rent	**M€**	187,80	196,15	196,15	153,43	167,08	168,63
Total SW	**M€**	1211,49	1192,06	1192,06	1019,69	1011,52	1010,04

Figure 36 shows how GEP investments are distributed in each case. As we can see in the PC case, there are bigger differences among each regulatory objective, while in the CO case the results are closer to each other. However, the investments in the CO case are always lower than the investment in the PC case. Please note that storage generation is almost non-profitable in the Cournot case, which is similar to the results in the 3-node Greenfield case. As mentioned before, these results are case dependent results, however, from several cases we have noticed that the CO cases tend to underinvest compared to the PC case, especially in BESS and wind while conventional generation and hydro investments tend to remain closer to the PC case. This could be explained, similarly to Section 0, because of the greater market power that BESS and wind can exercise when belonging to the same GENCO.

[39] Having in mind that the appropriate objective is welfare maximization

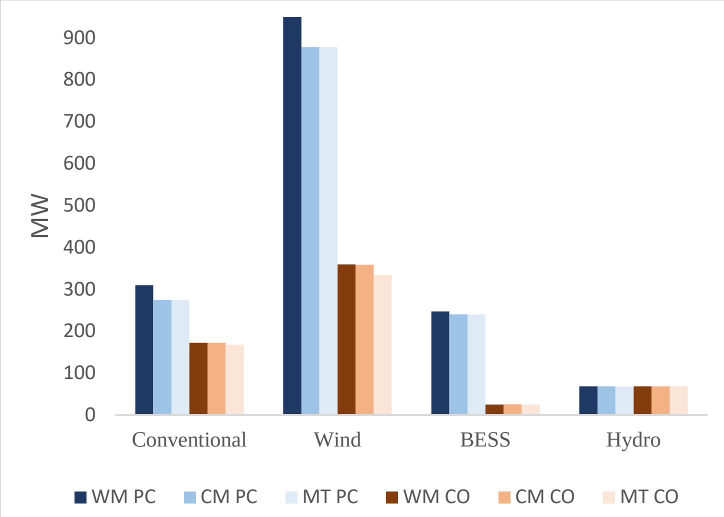


Figure 36: Generation Investment in Conventional Technologies, Wind, BESS and Hydro

Welfare Loss and Generation Mix Distortion

In this Section we compute the regret, as defined in 0, of disregarding market feedback in transmission expansion planning. The regret is computed as the welfare difference (relative the PM_CO) between the PM_CO case and the Actual CMM. Additionally, we also investigate how the generation mix changes under the different planning paradigms, and we compute the total GEP change by taking the difference between the GEP invested in the PM_CO and the Actual CMM relative to the existing generation capacity (4,32 GW).

Table XXXI: Proactive vs cost minimization: welfare and investment results

	Units	PM CO	Actual CMM	Difference (MW)	Difference (%)
	Lines	3-24/9-11	9-11		
Total TEP	MW	100	50	-50	-50
BESS	MW	92,34	93,78	1,44	1,56
	MWh				
Wind	MW	664,99	663,54	-1,45	-0,22
Thermal	MW	151,96	164,21	12,25	8,06
Total GEP	MW	909,29	921,53	12,24	1,35
Total SW	M€	1035,75	1034,15	1,60	**0,15**

Table XXXI shows the welfare and investment differences between the Actual CMM and the PM_CO. In this case, the Actual CMM invest only in line 9→11, which leads to 0,28% GEP overinvestment compared to the PM_CO case and a welfare regret of 0,15%. For this specific case these values are almost negligible, therefore in order to understand how these results vary among different system characteristics, we run a sensitivity analysis of the regret computation and the generation mix change. We examine different levels of the demand slope, from 0,50 €/MWh^2 to 1 €/MWh^2, and we consider different constrained systems by varying the capacity of all transmission lines from 40 MW to 65 MW.

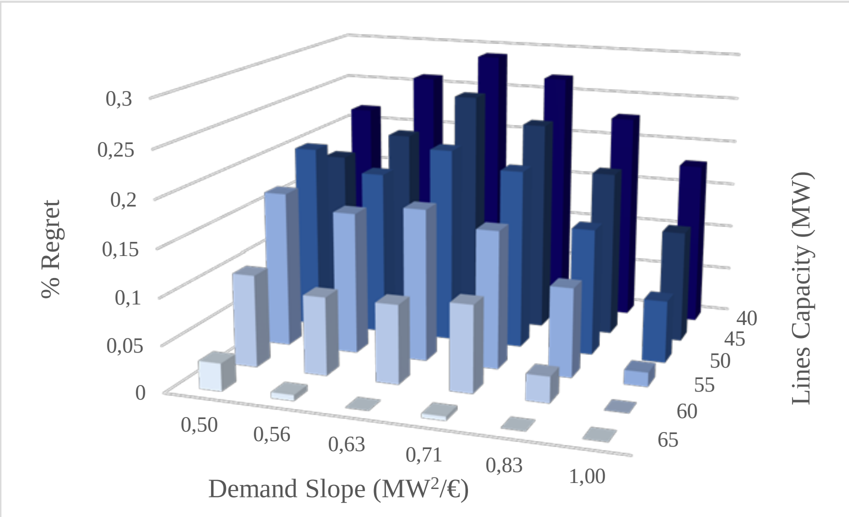


Figure 37: Regret Computation Sensitivity

As we can see in Figure 37, there is a non-linear relationship between regret and demand slope, and there is a non-linear but increasing relationship between regret and system congestion. Even though the percentage numbers of the regret seem relatively small (below 1% in the cases that we have studied here), in absolute terms the regret still ranges in the order of millions of euros. Therefore, disregarding strategic market feedback in a highly congested system can be considered a non-negligible planning regret, this result naturally follows, as a heavily congested system is more prone to present inefficiencies if no proper expansion is undergone. Additionally, there is not a clear evidence on how elasticity affects the regret of disregarding market feedback, but from Figure 37 we can see that low-congested systems are more sensitive to demand elasticity than highly-congested systems.

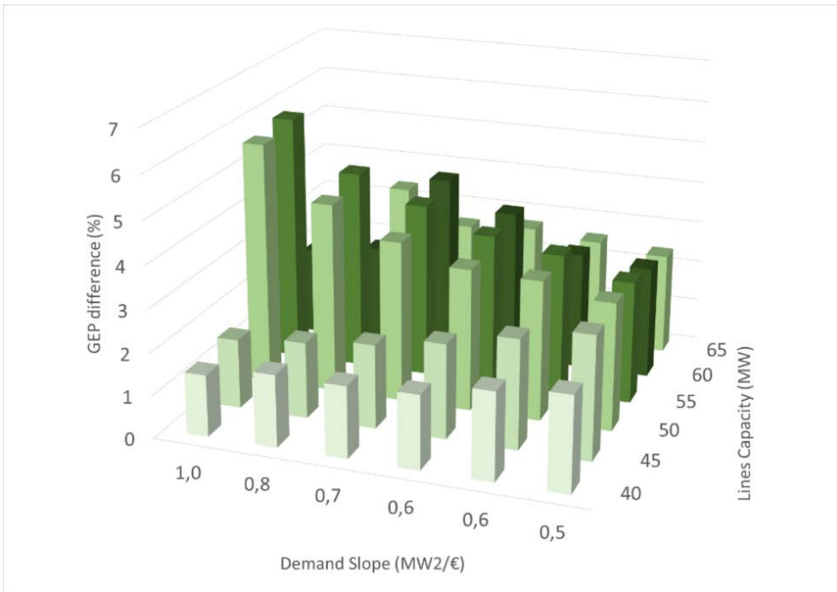


Figure 38: Generation Mix Sensitivity

The relatively small welfare regret, shown in Figure 37, can be somehow misleading if we do not investigate how the generation mix changes. Figure 38 shows how the generation mix changes depending on how constrained or elastic the demand in the system is. Figure 38 shows the existence of a distortion of the capacity mix, ranging from 1% to 7%. In particular, the highest generation-mix distortion is appreciated in mid-congested levels (50 MW and 55 MW transmission capacity) and elastic systems. Therefore, from the previous two graphs we can conclude that, TEP decisions made by a cost-minimizing TSO that disregard strategic market feedback will generate a relatively small welfare loss that tends to increase for highly constrained systems. In this specific case, the decisions of the cost-minimizing TSO will result in a significantly GEP overinvestment when there is a high demand slope, which will imply a higher welfare loss in the case of the most constrained networks.

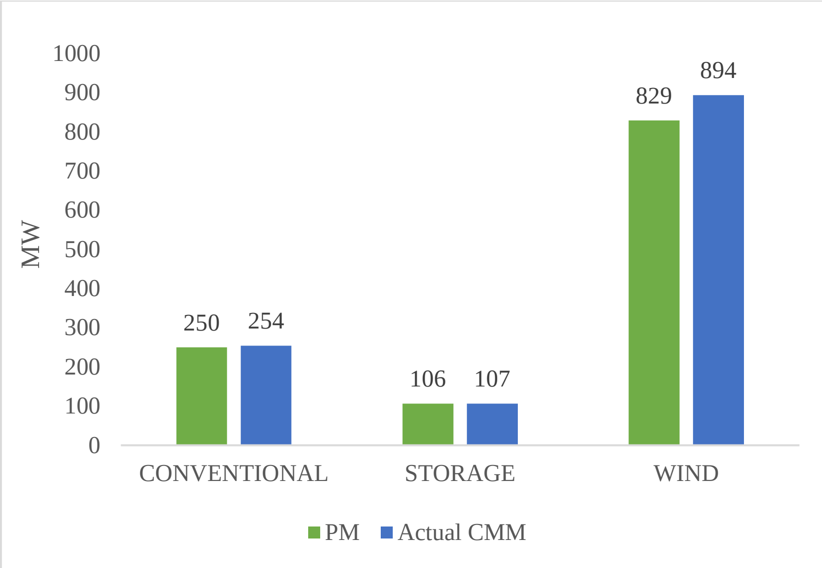


Figure 39: Generation Mix Distortion

From our sensitivity case we show, in Figure 39, the case with 55 MW capacity on transmission lines and a slope of 1 MW^2/€. In this case we can see a significant variation in the generation mix, which can affect the robustness of the system. In fact, in the Actual CMM, 60 MW of additional capacity is invested in wind generation, but only 1 MW (MWh) of storage and 4 MW of conventional generation (given a higher demand). This structure would react significantly different to variations in the wind availability that could lead to a high level of stress in the system implying a lower robustness.

In summary for this case study, one can conclude that disregarding market feedback might have a relatively small impact in terms of the overall welfare loss (which we referred to as regret); however, the subsequent impact on the optimal generation mix can be considered non-negligible. In this case study we have observed relative generation mix distortions of up to 7%. The distortion of the optimal generation capacity mix can, in turn, have important results on the robustness of the system. This detailed analysis is out of the scope of this paper.

Conclusions and Policy Implications

In this paper we proposed a model that represents generation and transmission expansion planning from the perspective of a proactive social planner. This social planner designs the system considering the feedback from either a perfectly competitive market or a Cournot oligopoly. Additionally, we considered also the formulation of a merchant investor that aims to maximize its congestion rents. As a novelty, we included investment and operation of long- (hydro) and short- (BESS) term storage systems.

This model allows us to study different policy issues. First, we evaluated the policy implications of planning the system under different objectives: either for a social planner (maximizing welfare, minimizing cost) or for a merchant investor (and maximizing congestion rents). We tested such planning objectives while considering either Cournot or perfect competition in the market. We concluded that the sub-optimal results of considering cost-minimization or congestion rent maximization are case dependent. In fact, we found that in some cases, a congestion-rent maximization can lead to the same welfare loss as a cost-minimization objective if there is some degree of demand response (through demand elasticity). Additionally, for the cases tested, under a Cournot oligopoly, we found that introducing a diversified generation portfolio for GENCOs leads to a better-off situation as it increases the competition among GENCOs.

Finally, we proposed a measure to evaluate the welfare loss of planning the system under the overly-simplistic view of a cost-minimizing vertically-integrated utility instead of a more realistic proactive framework that recognizes the possible strategic feedback (coming from GENCOs operation and investment decisions). We concluded that, if transmission planners disregard strategic market feedback in heavily constrained systems, there is a high chance that they will incur in a non-negligible welfare loss. Most importantly, this sub-optimal planning procedure also leads to a significant distortion of the optimal generation mix. This distortion can result in an over/under-investment depending on the system characteristics. Additionally, this sub-optimal generation mix can affect the robustness of the system, in terms of the responsiveness to intermittent resources availability. In future research we plan to explore those implications by extending the model and including uncertainty in the renewable sources. Moreover, alternative RES policy designs could be included in the transmission planner objective function to test more deeply how the social welfare can be affected.

5 Comparing Scenario-Based Transmission and Generation Expansion Planning Models for Imperfectly Competitive Markets Under Uncertain Wind Production

In this section we introduce the stochastic proactive GEPTEP co-planning problem by means a bi-level equilibrium model. This equilibrium (which is convex, because all constraints are linear) is re-formulated as a Mixed Integer Program (MIP), by replacing the lower level equilibrium constraints by its equivalent KKT conditions, and then by linearizing the resulting non-linearities. We present a 24-node case by comparing the deterministic, stochastic and min-max scenario based optimization under perfect and imperfect competition.

5.1 Notation

A. Sets / Indices

$y \in Y$	year
$w \in W$	scenarios
$p, \in P$	periods (hours in the year)
$ps \in Ps$	Moving window periods
$rp \in RP$	representative periods
$\Gamma_{rp,p}$	set of correspondence between rp and p
p	final period
$d, d' \in D$	nodes
$g \in G$	generator unit *g*
$t(g) \in T$	thermal units
$h(g) \in H$	storage units
$hf(h) \in HF$	fast short-term storage units (batteries)
$hs(h) \in HS$	slow long-term storage units (hydro)
$GAD(g,d)$	set of all possible *g* located at node *d*
$GED(g,d)$	set of existing g located at node *d*
$GCD(g,d)$	set of candidate g located at node *d*
$LA(d,d')$	set of all possible lines from node *d* to *d'*
$LE(d,d')$	set of existing lines from node *d* to *d'*
$LC(d,d')$	set of candidate lines from node *d* to *d'*
Hpp'	Univocal correspondence between period *p* and *p'* $\in \Gamma_{rp,p}$

B. Parameters

$pMaxProd_g$	Maximum capacity of technology g	MW

$pMaxFlows_{dd'}$	Maximum flow in line *dd’*	MW
$pReactance_{dd'}$	Reactance of line *dd’*	[p.u]
$pFCost_t$	Fuel cost of technology t	€/MWh
$pFixCost_t$	Fix operation cost of thermal generator	€
$pInvC_g$	Annualized investment cost g	€/MW
$pInvC_{dd'}$	Annualized investment cost of line *dd’*	€
$pDemand_{ypd}$	Demand Intercept at year *y* period p at node d	MW
$pDSlope$	Demand Slope	€/MW
$pEfficiency_h$	Efficiency of storage unit *h*	[p.u]
$pInfl_{yphsd}$	Energy inflows for year *y* period *p* storage *hs* at node d	MWh
$pMaxLevel_h$	Max/Min reservoir level of storage unit *h*	MW
$pMinLevel_h$		
$pMaxCons_h$	Maximum consumption of storage unit	MW
M	Time window	h
pW_{rp}	Weight of each representative day	[p.u]
pSB	Base Power	MW
θ_g	Conjectural variation of GENCO g	€/MW

C. Variables

$vProd_{ywpgd}$	Production at year y scenario w period p of generator g at node *d*	MW
$vNewGen_{ygd}$	Investment status at year y of generation unit g at node d	{0,1}/MW
$vNewLine_{ydd'}$	Investment status at year y of line connecting node d to d'	{0,1}/MW
$vFlows_{ywpdd'}$	Flows at year y scenario w at period p from node *d* to *d’*	MW

$vTheta_{ywpd}$	Voltage angle at year y scenario w period p node *d*	p.u.
$vDemand_{ywpd}$	Demand at year y scenario w period p at d	MW
$vLevel_{ywphd}$	Level at year y scenario w period p of storage unit h at node d	MW
$vConw_{yphd}$	Consumption at year $y$scenario w period p of storage unit h at node d	MW
$vSpill_{ywphd}$	Spillage at year y scenario w period p of storage unit *h* at node d	MW
λ_{ypd}	Prices at year *y* scenario w period *p* node *d*	€/MW

5.2 Model Description

Before presenting the formulation of the bi-level model, we first explain the market responsive framework to be used in the lower level. Then, we introduce the Bi-level Proactive Model (PM).

1. Market Responsive Framework

Following the work of [24], we consider an affine relation between prices and demand as shown in (105), i.e., demand is elastic, where *pDemand* represents the inelastic part of the demand and *pDslope* represents the slope of this function, which can be interpreted as how demand reacts to prices. Therefore, for a given node and period the demand would be given by (1).

$$vDemand_d = pDemand_d - pDslope_d * \lambda_d \ \forall d \qquad (113).$$

We furthermore define a conjectural variation $\theta_g = \partial\lambda_d/\partial vProd_g$ that is assumed to be known for every GENCO g . This conjecture corresponds to each GENCO's belief on how much they can impact market prices by varying its production $vProd_g$ (or $vCon_h$ for storage units). If $\theta_g = 0$ this represents perfect competition (PC), and if $\theta_g = 1/pDSlope$ (inverse of the slope of the residual demand curve) it represents the Cournot oligopoly (CO). This conjecture allows us to model different degrees of competitive behavior.

2. Deterministic Bi-level Proactive Model (DPM)

We present the proactive framework in which a social planner TSO - which can be understood as an entity where both TSO and regulator are considered together - (from now on TSO) proposes investments and GENCOs react to its decisions. Figure 40 shows the bi-level framework, where the TSO takes TEP decisions in the upper level subject to the lower level. Likewise, the lower level represents the market equilibrium where GENCOs take GEP and operating decisions, while the system operator (SO) makes sure that the power flow decisions are feasible.

<table>
<tr><td>Upper Level</td><td colspan="3">TSO or social planner
(decides TEP)
Maximizes Welfare</td></tr>
<tr><td rowspan="2">Lower Level</td><td>GENCOs
(decide GEP and operation)
Maximize Benefits</td><td>SO
(decides power flow)
Maximizes Congestion Rents</td><td>Consumers
(decide demand)
Maximize Demand Utility</td></tr>
<tr><td colspan="3">Market Clearing Condition</td></tr>
</table>

Figure 40: Bi-level Framework.

3. Stochastic Bi-level Proactive Model (SPM)

Please note that in Section 2 we consider that investment and operation are taken simultaneously in the lower level. This model, known as an open loop capacity equilibria, can render the same results as a close loop model (generation decisions first and then operation) only under certain conditions [13]. Even though the close loop equilibria is a more general framework, that considers the sequence between generation investment and operation, it leads to a more complex and intractable model. Therefore, in order to overcome the simplifications made by the open loop capacity equilibria we consider a two-stage stochastic generation expansion model in the lower level, which in turn leads to a stochastic proactive bilevel model, please see Figure 41.

We simplify the operation in the whole year by considering four representative days. Accordingly, we consider different wind profiles for each representative day, this implies considering daily the variability of wind along the year. However, wind can variate from year to year up to 20% from the mean (for the U.S western system), as seen from historical times series. Therefore, for each profile in each representative day we consider three scenarios (w), low, mean and high scenarios, which are 20% higher and lower respectively, in terms of energy, compared to the mean.

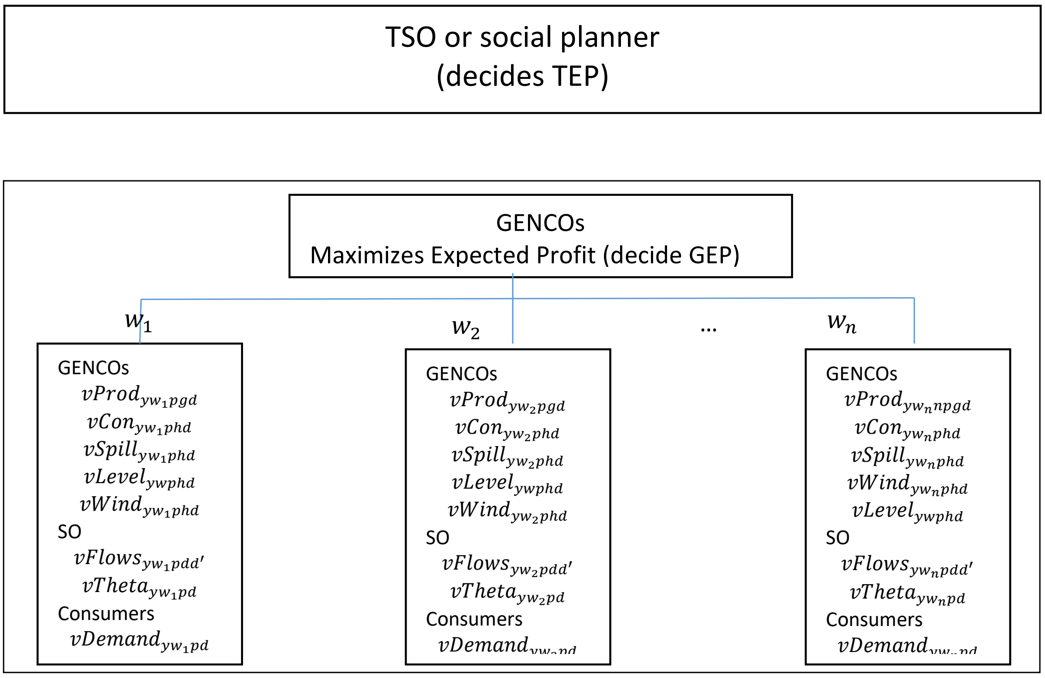


Figure 41: Stochastic Bi-level Framework

Upper Level: TEP

The social planner TSO aims at maximizing the total expected welfare, computed as the Utility of the Demand (UD) minus total costs. This objective is represented by (4), where central planner TSO minimizes the Total Cost (TC) composed by Line Investment Costs (LI), Generation Investment Costs (GI), and Operation Cost (OC). Therefore, the actual objective function would be given by (114). Note that we do not allow for de-investment as imposed by equations (117) and (118). Equation (115) represents the utility of demand resulting from the area under the demand curve.

$$\underset{vNewLineydd'}{\text{Maximize}} \quad UD - (OC + LI + GI) \tag{114}$$

Subject to (115) - (119), and Lower Level equilibrium

$$UD := \sum_{y,w,(p,rp)\in\Gamma_{rp,p},d} pProb_w * pW_{rp} * \left(pDemand_{ypd} * vDemand_{ywpd} - \frac{vDemand_{ywpd}{}^2}{2}\right) \tag{115}$$

$$OC: = \sum_{y,w,(p,rp)\in\Gamma_{rp,p},t,d} pProb_w * pW_{rp} * pFCost_t * vProd_{yptd} \tag{116}$$

$$LI := \sum_{ydd'} (Y - y + 1) * pInvL_{dd'} * \left(vNewLine_{ydd'} - vNewLine_{y-1,dd'}\right) \tag{117}$$

$$GI: = \sum_{gyd} (Y - y + 1) * pInvC_g \; * \left(vNewGen_{ygd} \; - \; vNewGen_{y-1,gd}\right) \tag{118}$$

$$vNewLine_{y-1,dd'} \leq vNewLine_{ydd'} \; \forall (d, d') \in LC \; \forall y \tag{119}$$

Lower Level: market equilibrium

The lower level represents the market equilibrium where consumers maximize the utility of the demand, GENCOs maximize their profits (deciding generation investment and operation of generating assets) and a SO maximize congestions rents (deciding power flows and voltage angles). The consumers, GENCOs and SO's optimization problems are linked by the market clearing condition (78). This market structure implies that GENCOs do not anticipate market outcome in their expansion decisions. However, as mention before, by introducing a two-stage stochastic model we are able to decide generation investment by considering different possible operation scenarios. Additionally, since we are able to adapt the degree of competition in the market in our model, choosing a less competitive market might "compensate" for this non-anticipation [25]. The previous description implies that the market is modeled as a spatial equilibrium model where GENCOs compete strategically and react naively to the transmission congestions as in [26]. Additionally, we assume that there is only one GENCO per node, but we might have several generation units per GENCO.

Moreover, in the formulation of the market model we use enhanced representative days [18] to represent the temporal structure. The novelty of this temporal representation is that it allows us to capture both short- and long-term storage technologies accurately due to the intra- and inter-day storage constraints, which are explained in detail in [18] and upon which we comment briefly later on. From now on, each equation is defined for $p \in \Gamma_{rp,p}$.(except (14)). Please note that $\Gamma_{rp,p}$ indicates which hours, from the whole year, belong to each representative day.

Consumer: Demand Utility maximization

The consumers try to maximize the utility of the demand, by deciding demand. Their optimization problem is given by:

$$Max_{vDemand_{ywpd}} \, UD$$

Subject to (115) and (120)

$$vDemand_{y,w,p,d} \geq 0 \; \forall ywpd : \iota_{y,w,p,d} \qquad (120)$$

GENCO: Profit Maximization Problem

$$arg \underset{GV}{\text{Maximize}} \, Profit = OI - OC - GI \qquad (121)$$

Subject to (116),(118), (122) - (14).

$$GV: \{vNewGen_{ygd}, vProd_{ywpgd}, vProd_{ywpgd}, vCon_{ywphd}, vSpill_{ywphd}\} \qquad (122)$$

(123)

$$OI := \sum_{y,p,rp,g,d} pProb_w * pW_{rp} * (\lambda_{ywpd}) * (vProd_{ywp,gd\in GAD} - vCon_{ywp,hd\in GAD})$$

(124)

$$0 \leq vProd_{ywpgd} \leq pMaxProd_g \quad : \bar{\rho}_{ywpgd}, \underline{\rho}_{ywpgd} \quad \forall ywp, \forall gd \in GED$$

$$0 \leq vProd_{ywpgd} \leq pMaxProd_g * vNewGen_{ywgd} \quad : \bar{\omega}_{ywpgd}, \underline{\omega}_{ywpgd} \quad \forall ywp, \forall gd \in GCD \qquad (125)$$

$$0 \leq vWind_{ywpgd} \leq pMaxWind_{pwgd} \quad : \overline{\rho w}_{ywngd}, \underline{\rho w}_{ywpgd} \quad \forall ywp, \forall gd \in GED \qquad (126)$$

$$0 \leq vWind_{ywpgd} \leq pMaxWind_{pwgd} * vNewGen_{ygd} \quad : \overline{\omega w}_{ywpgd}, \underline{\omega w}_{ywpgd} \quad \forall ywp, \forall gd \in GCD \qquad (127)$$

(128)

$$pMinLevel_h \leq vLevel_{ywphd} \leq pMaxLevel_h \quad : \overline{\mu e}_{ywphd}, \underline{\mu e}_{ywphd} \quad \forall ywp, \forall hd \in GED$$

(129)

$$0 \leq vLevel_{ywphd} \leq pMaxLevel_h * vNewGen_{yhd} \quad : \overline{\mu c}_{ywphd}, \underline{\mu c}_{ywphd} \quad \forall ywp, \forall hd \in GCD$$

(130)

$$0 \leq \frac{vCon_{ywphd}}{pEfficiency_h} \leq pMaxCons_h \quad : \overline{\kappa e}_{ywphd}, \underline{\kappa e}_{ywphd} \quad \forall ywp, \forall hd \in GED$$

(131)

$$0 \leq \frac{vCon_{ywphd}}{pEfficiency_h} \leq pMaxLevel_h * ETD * vNewGen_{yhd} \quad : \overline{\kappa c}_{ywphd}, \underline{\kappa c}_{ywphd} \quad \forall ywp, \forall hd \in GCD$$

(132)

$$-vNewGen_{y-1,gd} + vNewGen_{ygd} \geq 0 \quad : \underline{\beta}_{ygd} \quad \forall y, \forall gd \in GCD$$

$$0 \geq -vNewGen_{ygd}; 0 \leq MaxGen_g - vNewGen_{ygd} \quad : \bar{o}_{ygd}, \underline{o}_{ygd} \quad \forall yw, \forall gd \in GCD \tag{133}$$

$$0 \leq vSpill_{ypwhd} \; \forall yp, \forall hd \in GAD \tag{134}$$

$$vLevel_{ywph_fd} = vLevel_{y,w,p-1,hf,d} + pIniLevel_{y=1,w,p=1,hf,d} - vProd_{ywph_fd} + vCon_{ywph_fd}$$

$$: \psi_{ywphd} \quad \forall h_f d \in GAD, \forall ywp, p < pf \tag{135}$$

$$vLevel_{ywphsd} = vLevel_{y,w,p-M,hs,d} + pIniLevel_{y=1,p=1,hs,d} + \sum_{p'}^{p} \sum_{p''} (pInfl_{ywp''hsd} - vSpill_{ywp''hsd} - vProd_{ywp''hsd} + vCon_{ywp''hsd}) \tag{136}$$

$$: \psi'_{ywphd} \quad \forall yw, \forall hs, d \in GAD, \forall p, p < pf$$

$$with\ p` = p - M + 1\ and\ p \in Ps, p'' \in H(p', p'') \;\; Ps = \left\{ps | \frac{ps}{M} \in Z^+\right\}$$

Equation (59) represents the expected operational incomes of GENCOs, equations (60),(126), (130), (68) and (69) represent upper and lower bounds of the existing elements of the system. While equations (62), (15), (65) and (129) represent the lower and upper bounds of the candidate generation investments in the system. Equation (132) avoids de-investments and (67) defines the non-negativity of new generation. Finally, equations (13) and (14) represent the storage balance conditions as proposed in [18].

On the one hand, equation (14) is considered for long-term storage, i.e. hydro, where only interday balance is considered. In this equation, reservoir management is followed up across the entire year, as opposed to the rest of constraints in which only intraday operations are included. For the hydro vCon represents pumping decisions and vProd the production decisions. On the other hand, equation (13) is considered to represent short-term storage when intraday operation is relevant, i.e. batteries. Variables vCon and vProd represent charging and discharging. While the detailed formulation and explanation of this representation of storage is presented in [18], we briefly explain it here for clarity.

The reservoir energy balance is verified for a given time window. For instance, consider 4 representative periods, a 168 hour (one week) window and two weeks as shown in Figure 42. Thus, the reservoir balance equation (20) will be verified at the end of every week e.g. at M1 and M2. Thus, the interday balance is the sum of inflows and consumption minus spillage and production for every “representative hour” (p’’), which represents each hour of the year (p’). In addition, they are summed over the window M until hour ($p \in Ps$). Please note that $H(p'', p')$ maps each hour of the year to its corresponding hour in the appropriate representative day (i.e the first 24 hours of the year can be represented by hours 5545-5568 of RP4), and is not to be confused with $\Gamma_{rp,p}$ that tells us which hours of the year are the representative ones (i.e RP4 is made of hours 5545-5568).

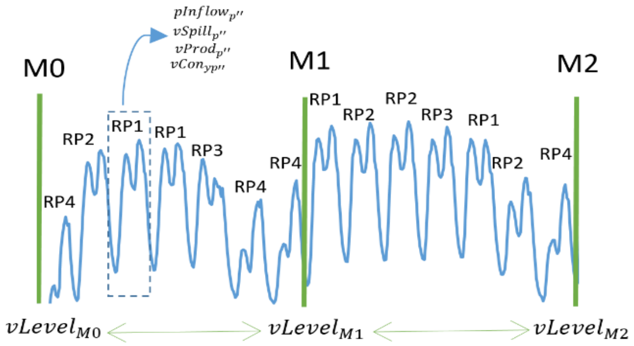


Figure 42: Interday Energy Balance**.**

<u>SO</u>

We assume that the SO wants to maximize congestions rents from price differences by deciding power flows.

$$arg \underset{vFlows_{ywpdd'}, vTheta_{ywpd}}{\text{Maximize}} \; CongestionRents = \sum_{y,p,d} (\lambda_{ywpd} - \lambda_{ywpd'}) * vFlows_{ywpd'd}$$

Subject to (72)-(77), where

(137)

$$pMaxFlows_{dd'} \geq vFlows_{ywpdd'} \geq -pMaxFlows_{dd'} \quad : \; \bar{\phi}_{ywpdd'}, \underline{\phi}_{ywpdd'} \forall ywp, \forall(d,d') \in LE$$

(138)

$$vFlows_{ywpdd'} = pSB * \frac{vTheta_{ywpd} - vThetha_{ywpd'}}{pReactance_{dd'}} \quad : \; \phi_{ywpdd'} \quad \forall ywp, \forall(d,d') \in LE$$

(139)

$$vFlows_{ywpdd'} \geq -pMaxFlows_{dd'} * vNewLine_{ywdd'} \quad : \; \underline{\zeta}_{ywpdd'} \quad \forall ywp, \forall(d,d') \in LC$$

(140)

$$-vFlows_{ywpdd'} \geq -(\; pMaxFlows_{dd'} * \; vNewLine_{ywdd'}) \quad : \; \bar{\zeta}_{ywpdd'} \quad \forall ywp, \forall(d,d') \; \in LC$$

$$-vFlows_{ywpdd'} \geq \left(-pSB * \frac{vTheta_{ywpd} - vThetha_{ywpd'}}{pReactance_{dd'}} - pMaxFlows_{dd'}\left(1 - vNewLine_{ywdd'}\right)\right) : \bar{\tau}_{ywpdd'} \;\; \forall ywp, \forall(d,d') \in LC \quad (141)$$

$$vFlows_{ywpdd'} \geq \left(pSB * \frac{vTheta_{ywpd} - vThetha_{ywpd'}}{pReactance_{dd'}} - pMaxFlows_{dd'}\left(1 - vNewLine_{ydd'}\right)\right) \quad : \underline{\tau}_{ywpdd'} \;\; \forall ywp, \forall(d,d') \in LC \quad (142)$$

Equations (72) and (73) represent the DC formulation of the network for existing lines, while equations (74)-(77) represent the DC power flow formulations for new lines.

Market Clearing

$$\sum_{g\epsilon GAD} vProd_{ypwgd} + \sum_{g\epsilon GAD} vWind_{ywpgd} + \sum_{d'\epsilon LA} vFlows_{ywpdd'} - \sum_{d'\epsilon LA} vFlows_{ywpd'd} : + \sum_{h\epsilon GAD} \frac{vCon_{ywphd}}{pEfficiency_h} = vDemand_{ywpd} : \lambda_{ypd} \; \forall y, w, p, d \quad (143)$$

The simultaneous consideration of the GENCOs, Consumers, SO, and market clearing condition represent the wholesale market for the case of perfect and imperfect competition (depending on the conjectural variation described in 4.1.1). Additionally, we implement a regularization method to compute Big Ms as proposed in [27].

KKT Conditions

An equivalent formulation for the lower level optimization problem is presented. KKT conditions are the following:

Primal feasibility conditions. SO: (72) - (78) and Gencos: (60) - (14)

Dual feasibility conditions. SO: (79) - (80) and Gencos: (81) - (87)

- Complementary slackness conditions[40]

Dual feasibility conditions: (Each equation is defined for $p \in \Gamma_{rp,p}$, except for equations

(83) to (87)

$$\begin{aligned} \lambda_{ywpd'} - \lambda_{ywpd} + \underline{\phi}_{ywpdd' \in LE(d,d')} - \bar{\phi}_{ywpdd' \in LE(d,d')} + \phi_{ywpdd' \in LE(d,d')} \\ + \underline{\zeta}_{ywpdd' \in LC(d,d')} - \bar{\zeta}_{ywpdd' \in LC(d,d')} + \bar{\tau}_{ywpdd' \in LC(d,d')} \\ - \underline{\tau}_{ywpdd' \in LC(d,d')} = 0 : vFlows_{ywpdd'} \quad \forall ywpdd' \end{aligned} \tag{144}$$

$$\begin{aligned} \sum_{d \in LE(d,d')} \frac{pSB}{pReactance_{dd'}} * \phi_{ywpdd'} - \sum_{d' \in LE(d,d')} \frac{pSB}{pReactance_{d'd}} * \phi_{ywpd'd} \\ + \sum_{d \in LC(d,d')} \frac{pSB}{pReactance_{dd'}} * \bar{\tau}_{ywpdd'} \\ - \sum_{d' \in LC(d,d')} \frac{pSB}{pReactance_{dd'}} * \underline{\tau}_{ywpd'd} \\ - \sum_{d' \in LC(d',d)} \frac{pSB}{pReactance_{d'd}} * \bar{\tau}_{ywpd'd} \\ + \sum_{d \in LC(d,d')} \frac{pSB}{pReactance_{d'd}} * \underline{\tau}_{ywpdd'} = 0 \\ : vTheta_{ywpd}, \forall ywpd \end{aligned} \tag{145}$$

$$\begin{aligned} \sum_{gyd} (Y - y + 1) * pInvC_g + \sum_{gyd} (Y - y) * pInvC_g + pMaxProd_g * \overline{\omega}_{ypgd} \\ + pMaxWind_{pwgd} * \overline{\omega W}_{ywpgd} + pMaxLevel_h * \overline{\mu c}_{ywphd} + pMaxLevel_h * ETD \\ * \overline{\kappa c}_{ywphd} + \underline{\beta}_{ygd} - \underline{\beta}_{y+1,gd} - \bar{o}_{ygd} + \underline{o}_{ygd} \\ = 0 \\ : vNewGen_{ygd} \quad \forall ygd \in GCD \end{aligned} \tag{146}$$

$$-vDemand_{ypd} + pDemand_d - pDSlope * vProd_{ywpgd} = 0 \tag{147}$$

$$\iota_{y,w,p,d} : vDemand_{ywpd} \quad \forall ywgd \in GAD$$

For equations

(83) to (87) we define $p'' = p' + 1 - M \; Pa = \{p | p \in \Gamma_{rp,p}\}$, $Ps = \left\{ps | \frac{ps}{M} \in Z^+\right\}$, $and \; Pt = Ps \cup Pa$

[40] Linearized conditions can be found in ANNEX

$$\left(\sum_{y,(p,rp)\in\Gamma_{rp,p},d} pProb_w * pW_{rp} * (-FuelCost_t + vProd_{ywpgd} * \frac{\partial \lambda_{ywpd\in(GAD)}}{\partial vProd_{ywpgd}} +)\right) + \lambda_{ywpd\in(GAD)} - \bar{\rho}_{ywpgd\in(GED)} + \underline{\rho}_{ywpgd\in(GED)} - \overline{\omega}_{ywpgd\in(GCD)} + \underline{\omega}_{ywpgd\in(GED)} + \sum_{p''}^{p'}(\psi_{yph}) = 0 \quad (148)$$

$$: vProd_{ywpgd} \quad \forall y,g,d \in (GED)\ \forall p' \in H(p',p) /\ \ p \in Pa,\ p' \in Ps$$

$$\left(\sum_{y,(p,rp)\in\Gamma_{rp,p},d} pProb_w * pW_{rp} * (\, vWind_{ywpgd} * \frac{\partial \lambda_{ywpd\in(GAD)}}{\partial vWind_{ywpgd}} +)\right) + \lambda_{ywpd\in(GAD)} - \overline{\rho w}_{ywpgd\in(GED)} + \underline{\rho w}_{ywpgd\in(GED)} - \overline{\omega w}_{ywpgd\in(GCD)} + \underline{\omega w}_{ywpgd\in(GED)} + \sum_{p''}^{p'}(\psi_{yph}) = 0 \quad (149)$$

$$: vWind_{ywpgd} \quad \forall y,g,d \in (GED)\ \forall p' \in H(p',p) /\ \ p \in Pa,\ p' \in Ps$$

$$\bar{\kappa}_{ywphd} - \underline{\kappa}_{ywgphd} + \psi_{ywph_fd} + \sum_{p''}^{p'}\left(\psi'_{ywphd}\right) = 0 \quad (150)$$

$$: vCon_{ywphd} \quad \forall p' \in H(p',p), p \in Pa,\ p' \in Ps, \forall yw, hd \in (GED)$$

$$-\overline{\mu}_{yphd} + \underline{\mu}_{yphd} + \sum_{p''}^{p'} \psi_{ywphd} = 0$$

$$: vSpill_{ywphd} \quad \forall p' \in H(p',p)\ \ p \in Pa,\ p' \in Ps, \forall yw, hd \in (GED) \quad (151)$$

$$-\overline{\mu e}_{ywphd} + \underline{\mu e}_{ywphd} - \overline{\mu c}_{ywphd} + \underline{\mu c}_{ywphd} + \psi_{ywp\in Pa,h_fd} + \psi_{yw,p+1\in Pa,h_fd} + \psi'_{ywp\in Ps,hd} - \psi'_{yw,p+M|p\in Ps,hd} = 0 \quad (152)$$

$$: vLevel_{ywphd} \forall p \in Pt, \forall ywhd \in GED$$

Equivalent Optimization problem

The KKT conditions in section 0 can also be written as an optimization problem by following the results of [28]. This optimization problem would be equivalent to minimizing the Extended Social Welfare and can be written as follows:

$$\underset{LLV}{\text{Minimize}}\, ESW = GI + OC + EC - UD \tag{153}$$

- *Subject to* ***(60) - (78) (154) - (159)***

$$LLV := \{vNewGen_{ygd}, vWind_{ywpgd}, vProd_{ywpgd}, vCon_{ywphd}, vSpill_{ywphd}, vFlows_{ywpdd'}, vTheta_{ywpd}\} \tag{154}$$

$$UD := \sum_{y,w,(p,rp)\in\Gamma_{rp,p},d} pProb_w * pW_{rp} * \left(pDemand_{ypd} * vDemand_{ywpd} - \frac{vDemand_{ywpd}^{2}}{2}\right) \tag{155}$$

$$EC := \sum_{y,w,(p,rp)\in\Gamma_{rp,p},t,d} pProb_w * pW_{rp} * \theta_g * (vProd_{ywp,gd\in GAD} - vCon_{ywp,hd\in GAD})^2 \tag{156}$$

$$OC := \sum_{y,w,(p,rp)\in\Gamma_{rp,p},t,d} pProb_w * pW_{rp} * pFCost_t * vProd_{yptd} \tag{157}$$

$$LI := \sum_{ydd'} (Y - y + 1) * pInvC_{dd'} * (vNewLine_{ydd'} - vNewLine_{y-1,dd'}) \tag{158}$$

$$GI := \sum_{gyd} (Y - y + 1) * pInvC_g * (vNewGen_{ygd} - vNewGen_{y-1,gd}) \tag{159}$$

As we can see the objective function is the same as a welfare maximization problem but it additionally includes EC which reflects the strategic behavior of agents by the conjectural variation θ_g.

4. Min-Max Regret Proactive Model (RPM)

We now compute a type of robust programing that considers the degree of robustness in the objective function. In this section we consider the min-max regret programming, this is an adjusted technique that is less conservative than the min-max programming where the system is planned against the worst case scenario. On the contrary, this framework tries to minimize the maximum regret of the solution in any operational scenario. We consider define the lower level and upper level min-max regret programming.

Lower Level Min-Max Regret (LLR)

We consider the min-max regret in the lower-level. Therefore, the regret is considered as the difference between the total Extended Social Welfare (defined in (40)) at each scenario ESW_s and the perfect information optimal solution $ESW^*{}_s$ of that scenario. By the perfect information solution scenario *s* we mean the solution of the Deterministic Proactive Model (DPM) when it is considered that only that scenario s will occur (i.e., *pProb(s)*=1). Compared to the stochastic approach, in this methodology we do not need to have a probability distribution of the scenarios.

$$\underset{LVV}{\text{Minimize}} \quad GI + \underset{s}{\text{Maximize}}(\, OC + EC - \; UD - ESW^*{}_s) \tag{160}$$

Problem **(160)** can be transform by adding the auxiliary variable ς and the set of equation **(162)**:

$$\underset{LVV}{\text{Minimize}} \quad GI + \varsigma \tag{161}$$

S.t and LL

$$OC + EC - \; UD - ESW^*{}_s \leq \varsigma \; \forall \; s \in S \tag{162}$$

Complete Problem with Lower Level Min-Max Regret

In the complete problem, the upper level would be constrained by the LLR defined in previous section.

$$\underset{vNewLineydd'}{\text{Minimize}} \; -(UD - (OC + LI + GI)) \tag{163}$$

s.t LLR

$$\underset{LVV}{\text{Minimize}} \quad GI + \varsigma \tag{164}$$

S.t (53) and LL

$$OC + EC - UD - ESW^{*}{}_{s} \leq \varsigma \; \forall \, s \in S \tag{165}$$

Upper level Min-Max Regret (ULR)

We consider the min-max regret in the lower-level. To do so, we follow the same logic in 0.Therefore, the regret is considered as the difference between the total Social Welfare (defined in (2)) at each scenario SW_s and the perfect information optimal solution $SW^{*}{}_{s}$ of that scenario.

$$\underset{vNewLineydd'}{\text{Minimize}} \; -(+LI + GI) \; + \underset{s}{\text{Maximize}}(\, OC - \; UD - SW^{*}{}_{s})$$

Complete Problem with Upper Level Regret

$$\underset{LVV}{\text{Minimize}} -(+LI + GI) + \varsigma \qquad (166)$$

S.t **(167)** and LL

$$OC - UD - SW^{*}_{s} \leq \varsigma \; \forall \, s \in S \qquad (167)$$

5.3 Case Study

In order to test this model we consider a IEEE-24 modified system as the one considered in [10]. As seen in **Figure 40** this system is made up of 24 buses, 33 existing lines, and 12 existing conventional generators. Continuous lines represent existing elements and dotes lines represent candidates lines. We consider 3 candidate conventional generators at nodes 3, 10, and 19, as well as 6 wind candidate generators at nodes 3,5,7, 16,21,23. Additionally, we consider 4 candidate batteries at nodes 1, 3 ,15 and 1 hydro candidate at node 19.

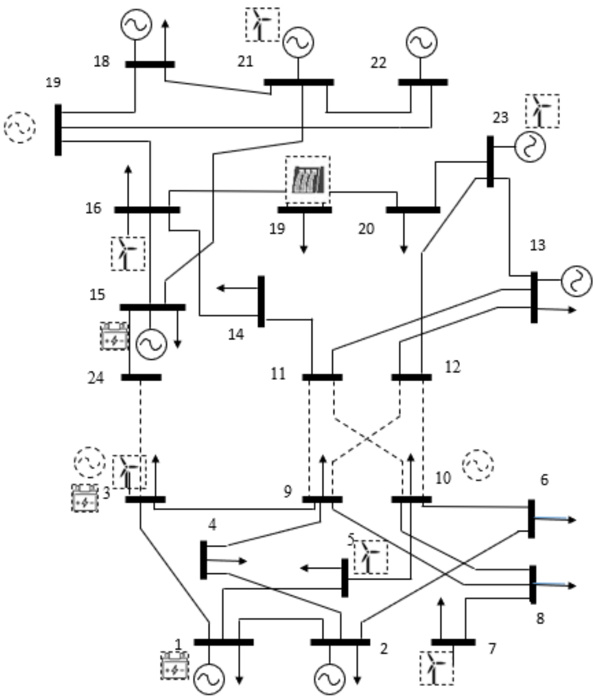


Figure 43: IEEE-24

We consider 4 representative days and 3 wind profiles scenarios for each wind candidate generator. We consider different profiles for the wind generator located at the south (nodes 3,5,7), as seen in Figure 44: Southern Normalized wind profiles per GeneratorFigure 44, and some other profiles for those located in the north (nodes 16,21,23) as seen in Figure 45.

We consider the following probabilities for the scenarios:

Table XXXII: Scenarios Probability

S1	S2	S3
0.24	0.38	0.38

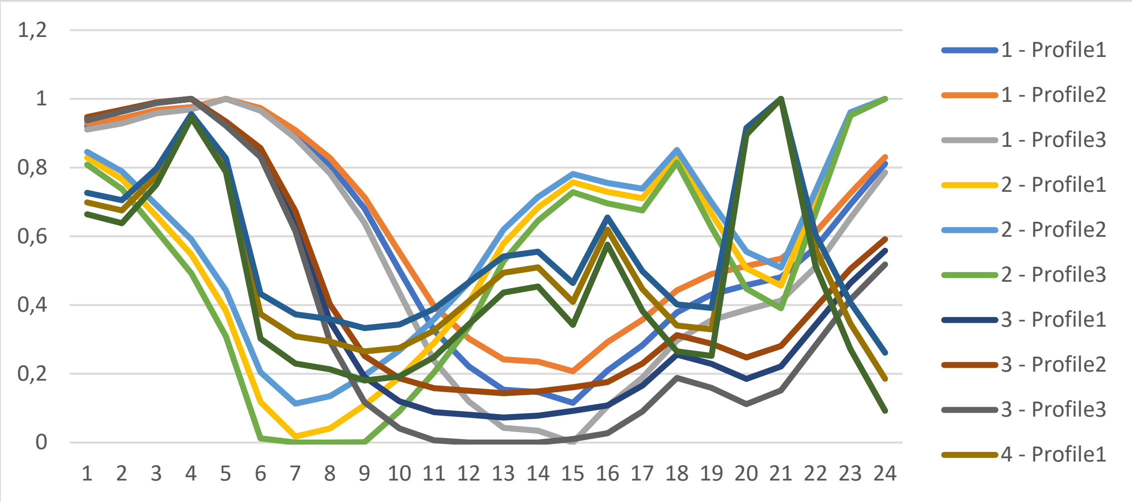


Figure 44: Southern Normalized wind profiles per Generator

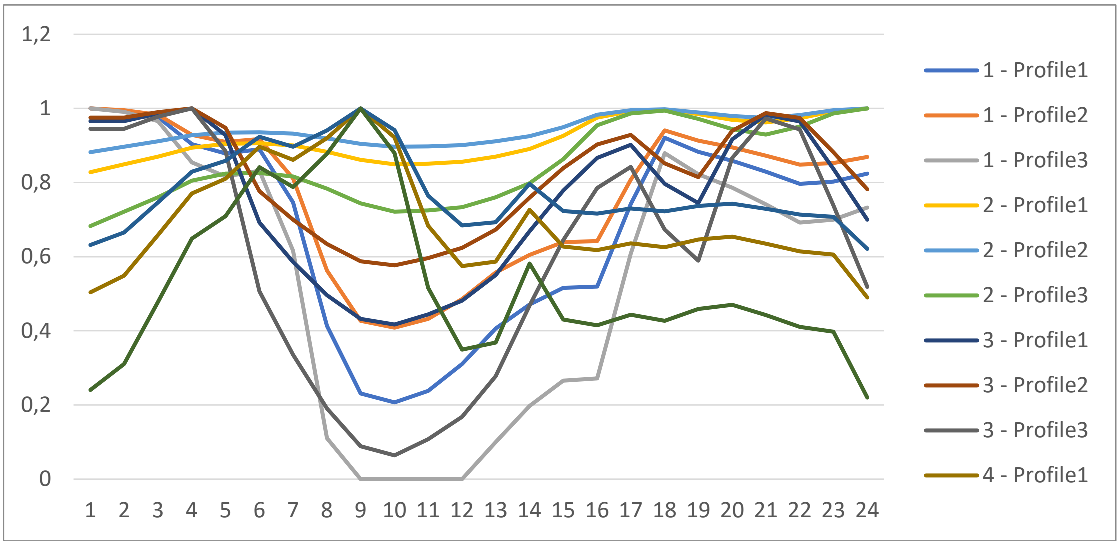


Figure 45: Northern Normalized wind profiles per Generator

5.4 Results

We initially study the planning results when considering perfect competition or Cournot oligopoly in the lower level, both for the deterministic and stochastic case. We thus define six different types of problems:

Deterministic Perfect Competition (DT-PC), Deterministic Cournot Oligopoly (DT-CO), Stochastic Perfect Competition (ST-PC) and stochastic Cournot Oligopoly (ST-CO).

Table XXXIII: Cases Definition

DT-PC	DT-CO	ST-PC	ST-CO	RM-PC	RM-CO
Deterministic optimization with perfect competition in the lower level	Deterministic optimization with Cournot oligopoly in the lower level	Stochastic optimization with perfect competition in the lower level	Stochastic optimization with Cournot oligopoly in the lower level	Minimizing Maximum Regret with perfect competition in the lower level	Minimizing Maximum Regret with Cournot Oligopoly in the lower level

In Figure 46 we see the total capacity invested in wind and storage technologies for every case. Please note that the Wind capacity is divided by 10 in the graph (scaling purposes). First, only one line is invested for the Perfect Competition (_PC) cases, there is lower investment in wind and therefore higher investment in storage compared to the Cournot Oligopoly (CO) case. This result can be explained because in the CO case no transmission line is built and therefore more generation capacity is needed to supply the demand. Additionally, in general the capacity invested in the stochastic (_SC) cases is lower than in the deterministic (DT). This is clearly seen because the higher variability of wind profiles makes the wind investment less profitable. . It is interesting to note he RM scenario is the most extreme case, where there is PC it is the scenario with the highest investment while in the CO case it is the one with the lowest investment, this suggest that in the CO case the best way minimize the maximum regret is to install the lower wind and storage capacity to limit the market power while in the PC case installing more capacity leads to minimize the regret as the capacity would be optimally utilized.

We now compare the results in terms of the expected social welfare. As seen in Figure 47. The total welfare is higher in the PC cases compared to the CO cases, in part this is given because more demand in supplied in the PC case compared to the CO case. Additionally, the producer surplus is higher in the CO case than in the PC case. Finally, please note that the difference in the total welfare between the deterministic, min-max regret and stochastic case is very small, it accounts to less than the 0.1%, while there is a difference of the 10% between the PC cases compared to the CO case. This might suggest that, for this case study, the imperfect competition has a higher impact on the system planning than the uncertainty of the renewable sources.

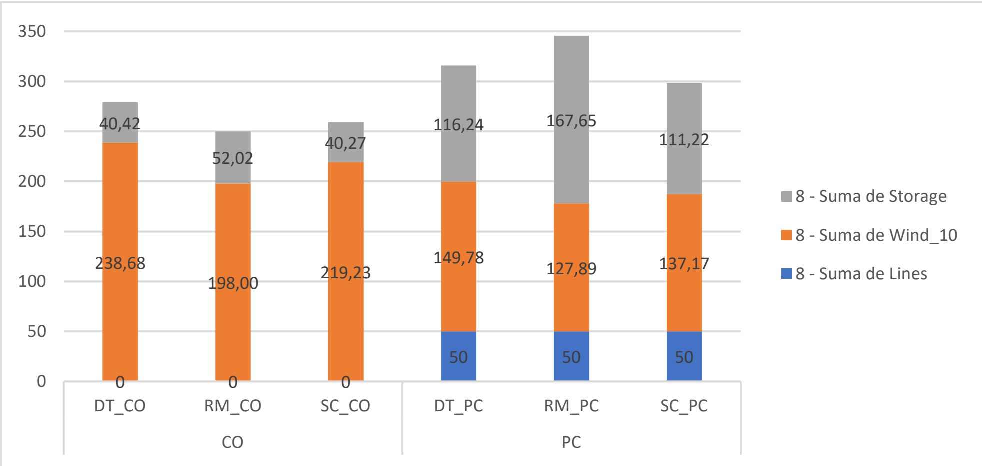


Figure 46: Capacity Invested

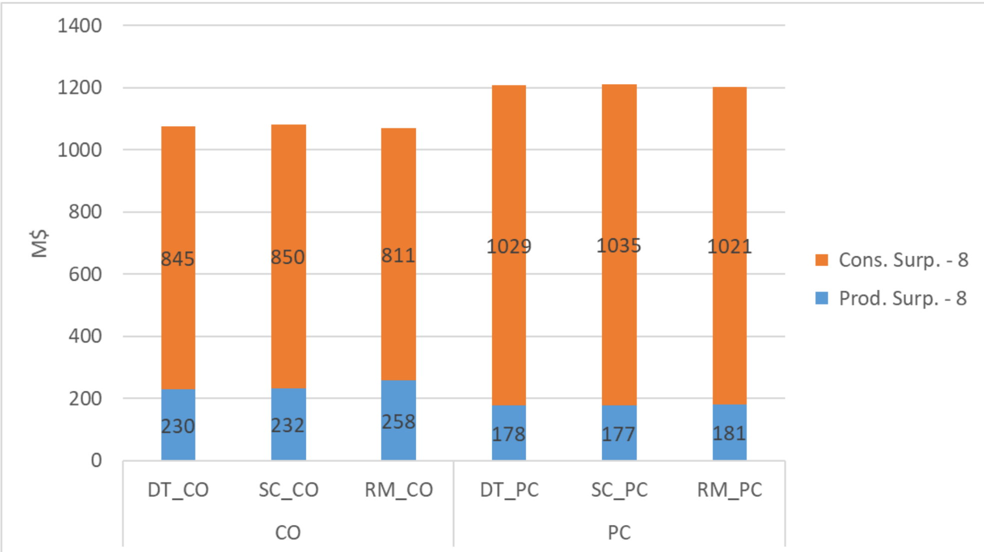


Figure 47: Total Surplus

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Santa Cruz de Marcenado, 26
28015 Madrid
Tel +34 91 542 28 00
Fax + 34 91 542 31 76
secretaria.tecnica@iit.comillas.edu
www.iit.comillas.edu