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IMPACT OF THE INTEGRATION OF OPERATING CONSTRAINTS OF THERMAL GENERATION ASSETS IN ELECTRICITY MARKETS MODELS

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Impact of the integration of operating constraints of thermal generation assets in electricity markets models

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Abstract

Balancing energy markets are currently being implemented in the European power system, progressively replacing historical balancing processes that were designed at a local scale. Occurring within the last hour before real-time, these markets are consequently subject to specific constraints. Amongst these, operating constraints applied to generation and consumption units heavily conflict with the order formulation process of market actors. This paper curates a list of operating constraints–particularly related to thermal units–relevant to the balancing time frame, before highlighting the incomplete inclusion of these constraints in common energy market models. It then proposes a modeling approach that incorporates them in the electricity market agent-based model ATLAS, and demonstrates the impact of each one through a case study on the 2030 European power system. Results show that modeling operating constraints leads to a significant decrease of market liquidity (up to 60%), and to subsequent impacts on market performances (notably a 114% increase in balancing costs and a doubling of the volume of unsupplied Transmission System Operator balancing demand). This advocates for the relevance of the inclusion of these constraints in balancing market models, and puts into perspective results obtained without them.

Keywords: Balancing energy markets, Replacement reserves, Harmonised balancing products, Electricity market modeling, Operating constraints.

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I INTRODUCTION

European power systems have been undergoing a gradual liberalization since the beginning of the 21^{st} century, with the creation of electricity markets ever closer to real-time. The day-ahead spot market was implemented first, followed a few years later by the intraday market. These two markets were progressively extended to include more European areas. The intraday market was, until recently, the closest to real-time large-scale common market[1]. Indeed, during the period between the last intraday market and real-time, Transmission System Operators (TSO) are legally in charge of maintaining a balance between supply and demand, and were historically achieving this task by activating balancing reserves through local processes. European TSOs used diverse balancing processes tailor-made for their local area, with notable design differences in terms of market order type, clearing process or remuneration scheme. Various studies illustrate the deeply heterogeneous aspect of these processes ([36], [37], [16], [31]). This state of balancing processes in Europe presented both advantages and potential inefficiencies. On the one hand, they were adapted to the specific features of the local power system, and consequently able to able to align the best with the technical constraints of the regional options. On the other hand, interconnected markets could achieve better economic performance thanks to a larger pool of offers and provide a more transparent and harmonized design.

To address these inefficiencies, the European regulation proposed to take another step in the path of liberalization by creating common European balancing markets, revolving around harmonized types of balancing reserves:

- Frequency Containment Reserve (FCR) that aims to stop any frequency deviation, by an automatic and proportional reaction to frequency deviations within a few seconds.
- automatic Frequency Restoration Reserve (aFRR), corresponding to the automatic activation of units within a few minutes to restore the frequency to its initial level.
- manual Frequency Restoration Reserve (mFRR), which serves the same purpose as aFRR but is activated manually in under 15 minutes.
- Replacement Reserve (RR) is eventually activated manually under 30 minutes to replenish all reserves described previously.

These reserves are part of a two-stage process: (i) a procurement stage taking place a few hours up to months before real time[2], during which both upward and downward power capacities are locked to make sure that enough reserves will be available in real-time, and (ii) an activation market occurring in real-time, which activates balancing energy to meet supply-demand imbalances. Because of the differences in time scales and activation methods (manual versus automatic), the set of technical and dynamic constraints associated with mFRR and RR reserves is quite distinct from that of aFRR

[1] Interzonal balancing markets existed in the Nordic area, but were not entirely homogeneous and harmonized [22]

[2] FCR reserves are procured as at European scale. Currently, the procurement of all other reserve types is still managed locally by TSOs, as there is currently no common European procurement market for it. This explains the diversity in terms of procurement timing.

and FCR reserves. This study does not look at the procurement stage, and focuses entirely on the activation of manual balancing reserves, traded on common cross-border platforms. On these platforms, Balancing Service Providers (BSPs) submit upward and downward reserve orders that correspond respectively to an increase and a decrease in power generation, whereas TSOs submit orders according to their balancing needs, computed using imbalance forecasts on their area. As Section II will show, the overall design of these markets has already been defined. The existing literature on balancing markets discussed the optimal choices of variables and parameters of this design (for instance schedule time unit, gate closure times, method of procurement, balancing service pricing mechanisms, activation strategy or order requirements), and indicated the subsequent economic benefits of balancing markets compared to previous processes, notably significant gains in terms of balancing costs.

However, studies of this literature were mostly conducted on simplified models that do not accurately represent the complexity of generation units and their operating constraints, although these constraints have strong interactions with the order formulation process of balancing markets. Indeed, the high degree of order standardization required for operating a common European market limits the shape of market orders that can be submitted by both TSOs and BSPs. To comply with both order standardization and their operating constraints, BSPs often have to adapt the volume of balancing energy offered in their orders, and have to rely on several types of links between them–called order couplings–that add an extra level of complexity to market processes. Taking into account this phenomenon can influence simulation results, which directly impacts expected benefits and optimal design recommendations made by aforementioned studies.

The research question of this paper is thus the following: how do the operating constraints of thermal units impact balancing market performances, especially on indicators discussed in previous studies, and is their representation in market models relevant? We chose to focus on thermal units to narrow the study to a reasonable number of operating constraints, while still studying a unit type that is heavily influenced by these constraints.

Studying this question leads to three main contributions to the literature. First, a literature review provides an overview of the theoretical design of balancing markets and their expected benefits, and establishes a list of relevant operating constraints for thermal units, as well as the state of their integration in balancing market models (Section II).

Then, a model designed to emulate RR and mFRR markets is proposed in Section III. It is integrated within the agent-based model ATLAS (exhaustively described in [24] and [6]), and it includes a detailed representation of operating constraints, by modeling with precision:

- The whole balancing process, starting from the market order (i.e. market bids) formulation by all market actors, followed by the Market Clearing stage, and eventually leading to a portfolio optimization done for each BSP to create generation programs. Additionally, a final local balancing process can be run after

balancing markets to compensate for any remaining imbalance. It is based on the historical French Balancing Mechanism (FrBM).
- A detailed European power system including a diverse core of generating units, as well as an exhaustive list of operating constraints specific to the different types of units.
- The design chosen for each cross-border platform, along with the possibility of linking market orders during their formulation to account for operating constraints, and methods used to address these coupling links during the Clearing stage.

Finally, this model is applied in a case study that investigates the impact on market performances of integrating operating constraints in market models, looking at each constraint individually and also at their simultaneous inclusion. The methodology is detailed in Section IV, and the results of this study are discussed in Section V, showing significant impacts on both market liquidity and outcomes.

II LITERATURE REVIEW

Our literature review focuses on two main aspects: it first gives an overview of previous studies assessing the potential benefits of cross-border balancing markets, or in analyzing their optimal design, and then details which operating constraints are relevant when looking at balancing markets and how they are taken into account in models of the literature.

2.1 Expected benefits of common balancing markets

Several theoretical reasons for transitioning from local processes to common markets are presented in the literature. First, coupling multiple areas together offers two main advantages. A larger pool of orders should result in the activation of cheaper units, as was previously shown by [9] on the balancing reserves procurement market in the northern region of Europe. A common market also functions as a built-in netting system that will avoid activation of reserves of opposite directions (i.e. upward and downward) from interconnected areas that share non-saturated transmission lines, which is studied by [43] for instance. On top of theoretical gains from area coupling, the transition to common markets gives the opportunity to define a common optimal architecture, regarding design variables such as the order selection method, the pricing method, the gate closure time, or the schedule time unit of the market ([7] and [14]). Finally, another key benefit is the improvement of market transparency. These last two points will notably be crucial to the integration of renewable energy sources by allowing their participation in the balancing process, through which they can mitigate the increase of balancing needs that they are expected to induce ([42], [18] and [23]).

As explained in [30], there are two main methods for evaluating the benefits of market integration: simulations using scenarios that incorporate different levels of integration, and the analysis of interconnector capacity usage based on empirical and projected data. The latter is chosen by the authors, and they concluded that coupling balancing energy markets in Europe could lead to considerable benefits (up to €2.4 billion/yr). It was also used in the study [27] that empirically shows that the benefits of the transition from bilateral contracts to an auction-based market in day-ahead that occurred in 2004 in the US area of PJM outweigh the costs it induced. However, the main focus of our article is the simulation approach, which is the most common in the literature according to [30].

The standard method for estimating gains resulting from market evolution is the analysis of social welfare, which corresponds to the sum of the surplus of all market actors. This concept is broadly used for analyzing the day-ahead market (see [26] or [30]), but remains rather unexplored in the exact context of balancing markets, as explained in [46]. In this article, the author details the computation method of social welfare, and justifies its theoretical increase from coupling areas together, although no practical application or quantified gain is given. To our knowledge, no further study has been conducted on this topic. A possible explanation lies in the difficulty of estimating the surplus of TSO demands. In [46], the demand for balancing energy is supposed to be inelastic, and TSOs are assumed to have a preference price for their market orders. These assumptions could first be challenged, and in any case the preference price is difficult to determine properly, rendering the overall welfare computation problematic (see Section 5.2.2 for more details).

Expected benefits are consequently usually presented in the form of TSO balancing cost reduction. Reference [45] compares 3 local balancing markets (corresponding to Italy, Austria and Slovenia) to a common one. The overall balancing cost reduction in the coupled scenario is estimated at 55%, while noticing different patterns in each area: costs are actually increasing in Austria and Slovenia, and are heavily decreased in Italy. Similar studies based on the Nordic area (including Norway, Sweden, Finland, Denmark, the Netherlands and Germany) can be found in [1] and [13], where the yearly balancing costs are estimated to decrease by resp. 55% and 75% when energy markets are integrated. [43] focuses on the netting aspect, and shows qualitatively the benefits of an Area Control Error netting.

2.2 Theoretical discussion and current design of the RR market

A wide range of studies look at the theoretical optimal design of these new balancing markets. [44] summarizes the different components and parameters of a market design, details commonly discussed choices for these parameters, and defines metrics that can be used to compare several designs. The authors determine 9 different performance criteria covering various themes (security of supply, economic efficiency, market facilitation).

In addition to this framework, research was also conducted to identify optimal values for nearly all design parameters. To only cite a few:

- [43] illustrated the optimality of the selection of units according to a Common Merit Order List (CMOL).
- Regarding the choice of pricing method, several articles compare particular marginal pricing and pay-as-bid pricing, and conclude that the marginal pricing is economically more optimal since it encourages generators to bid at their generation costs, and leads to lower costs for consumers ([42] and [3]). This is completed by [44],

who added that a higher clearing frequency would likely lead to lower balancing prices in the case of marginal pricing.
- The Imbalance Settlement Price (ISP) is another commonly studied topic, even if it is currently not part of the design of cross-border platforms of RR and mFRR reserves[3], with [17] concluding that this parameter is highly impactful on the performance of all electricity markets, even those further from real-time such as the Day-Ahead market.
- As a last example, [34] considered different Gate Closure Times (GCT) for BSPs, corresponding to the deadline past which they cannot submit market orders anymore. The study demonstrated that a GCT of 60 minutes is better than a GCT of 15 minutes based on both the volume of balancing energy activated and overall balancing costs. This is largely due to BSPs' limited information about the current and future states of the whole power system, compared with a central actor.

As the case study of this paper focuses on the existing RR market, an overview of the design is provided (see [8] for more details). For a given occurrence of the market that spans on a time frame that we will call T_{RR} (corresponding to the actual period of reserve activations), the following process is applied and illustrated in Figure1:

1. BSPs submit all their market orders to their respective TSO before their GCT, which varies between areas but is comprised between 60 and 50 minutes before the beginning of T_{RR}.
2. TSOs then transmit these orders along with their balancing needs to the TERRE market platform, before the TSO-associated GCT (which is universally set to 40 minutes before T_{RR}).
3. Market orders are selected and activated using a CMOL, and the market price is determined according to the marginal pricing method.
4. Eventually, market results are sent back to all actors 30 minutes before T_{RR}, and BSPs adjust the power output or the load of their portfolio to meet activation requirements.

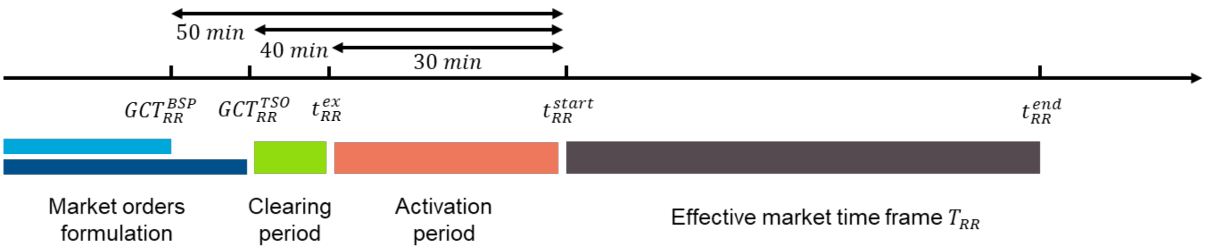


Figure 1: Illustration of the RR market time frame

Setting up a European cross-border market also requires a high degree of standardization, in particular for the shape of market orders that can be traded. The standard for RR market order is described in Table 1, associated with a schematic representation of a market order in Figure 2 that illustrates characteristics noted 1 to 5 in the table.

[3] It is still managed locally by TSOs.

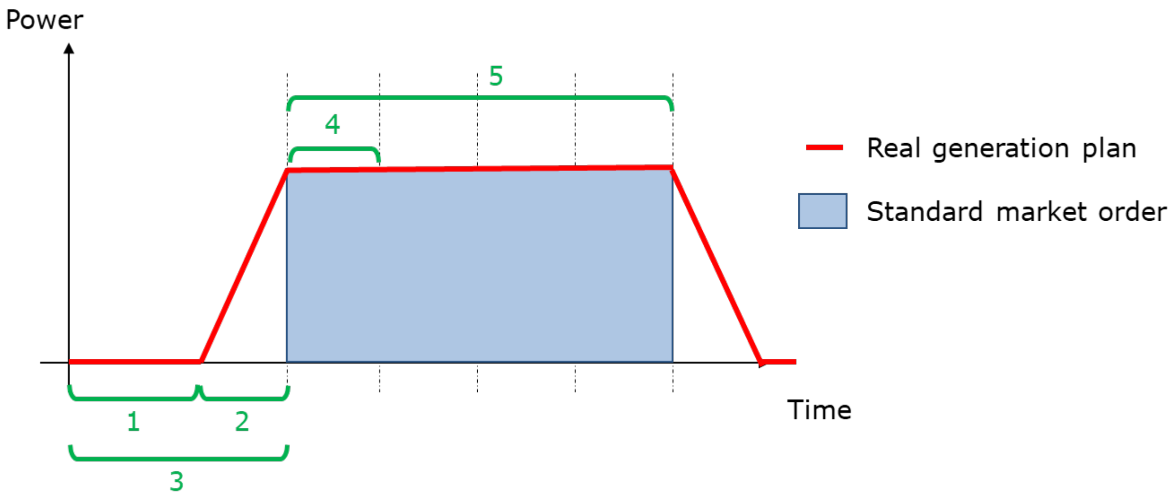


Figure 2: Schematic market order representation

Characteristic	BSP order	TSO order
Preparation period (1)	Between 0 and 30 min	/
Ramping period (2)	Between 0 and 30 min	/
Full Activation Time (3)	30 min	/
Minimum duration (4)	15 min	15 min
Maximum duration (5)	60 min	60 min
Minimum quantity	1 MW	1 MW
Maximum quantity	/	Up to the quantity of bids of opposite direction submitted by BSPs in the TSO's area
Minimum price	-10,000 €/MWh	-10,000 €/MWh
Maximum price	10,000 €/MWh	10,000 €/MWh
Price resolution	0.01 €/MWh	0.01 €/MWh
Order divisibility	Fully divisible Partially divisible Indivisible	Fully divisible
Coupling links permitted[4]	Exclusive Multi part Linked in time	Linked in time

Table 1: RR market standard product

The Preparation period, Ramping period and their sum, corresponding to the Full Activation Time (FAT), set an upper limit to the delivery duration: starting when market results are sent back to the actors, an order is required to deliver the activated quantity within the FAT, and can modulate its Preparation and Ramping periods at will in order to respect it. This only concerns physical units, and therefore is not relevant to TSO orders. A specific requirement is applied to the maximum quantity of TSO orders: it is limited by the sum of power of all orders submitted in the opposite direction by BSPs in

[4]See Section 3.1.1 for details about coupling links and how they are translated in the model

their area. For instance, if the total volume of sale (resp. purchase) orders formulated by BSPs in the area of a given TSO is equal to 70 MW, it will not be able to submit a purchase order (resp. a sale order) of more than 70 MW, regardless of the imbalance volume it has computed. Minimum and maximum durations impose boundaries on the length of a market order. In the RR market, an order cannot last for less than 15 minutes and cannot exceed the total duration of the market time frame (60 minutes).

2.3 Operating constraints and their interactions with electricity markets

Previous sections illustrated the fact that the theoretical design of balancing markets and their expected benefits is already largely discussed in the academic literature. However, most studies tend to oversimplify certain operational or practical parameters, which may have a considerable impact on market performance. In particular, they usually only consider a few operating constraints on generating units, if any, and do not take into account the coupling links created between market orders by BSPs to represent these operating constraints.

[29] provides a list of operating constraints that are used in advanced thermal unit commitment problems:

- **Maximum power** output.
- **Minimum power** output, which is often strictly positive in the case of thermal units and implies a concrete distinction between the OFF state (during which the power output of the unit is 0) and the ON state (for which the power output of the unit is between its minimum and maximum power).
- **Maximum ramping**, imposing a ramping limit when increasing or decreasing the power output.
- **Minimum time ON**, indicating that the unit should be ON for at least a certain period after being started.
- **Minimum time OFF**, indicating that the unit should be OFF for at least a certain period after being shutdown.
- **Startup duration**, the duration required for the unit to go from an OFF state to its minimum power.
- **Shutdown duration**, the duration required for the unit to go from its minimum power to an OFF state.

The first 3 constraints of this list are the most basic ones. [26] already highlighted their impact on market performances, and they were later included in most existing studies and models as Section 2.4 discusses. They are also not specific to thermal units, as opposed to the subsequent constraints.

In addition, [34] models the following constraints:

- **Minimum stable power duration** for all thermal units, which indicates that the unit must keep a stable power output for a certain duration before ramping up or down again.
- **Notice delay**, representing the period required by a unit between the decision of a program modification (for instance a startup, or even a simple modification of the power output) and the moment when this unit is actually able to begin

this modification. This corresponds to the Preparation period in the glossary in Table 1. Authors include this operating constraint in their representation of both thermal and hydro units, and it could be justified for demand flexibility as well.

Because of the prevalence of operating constraints for thermal units compared to other types of units, this study will focus solely on them. Nonetheless, constraints also exist for almost all unit types. In most models, hydro power plants take into account a maximum level for their water reservoir. Some include a minimum level as well, which may be different from 0 because of regulatory restrictions. In contrast, for Pumped Hydro Storage (PHS) plants, the transition duration constraint when switching between pumping and turbining states is, to the author's knowledge, never considered in any of these models. The impact of this constraint could be studied later on using ATLAS, as it is already modeled in it. Demand response may also be constrained, mainly by daily energy limits, load postponement requirements or even significant notice delay for some categories of load units. However, these constraints are deeply heterogeneous amongst the wide variety of load units, and also difficult to evaluate because of a lack of empirical analysis. Storage units such as batteries are subject to storage level constraints and to charge and discharge efficiencies, which are usually modeled in the literature. Finally, renewable energy sources are only constrained by their ability to curtail their power output. Overall, the diversity of operating constraints, and its dependence on the unit type, implies that the generation mix plays a considerable role in the complexity of markets.

All these constraints become increasingly restrictive for close-to-real-time markets such as balancing markets, as they interact with standardization requirements detailed in Section 2.2 in two major ways:

- By restricting the power that can be offered by certain types of units on markets, or in the worst case entirely preventing them from participating. For instance, this would be the case for a unit that has a minimum stable power duration constraint greater than 60 minutes, as it would not be able to comply with the RR maximum duration constraint described in Table 1.
- Even for units that are able to formulate market orders, it is often still necessary to create "complex" orders to reflect their operating constraints. A unit with a minimum stable power duration of 30 minutes would be able to offer reserves on the RR market, but only over two consecutive time steps. This implies additional consideration: across which time steps to submit the offer, and how to manage interactions with other formulated offers.

The example given in the second point only demonstrates a specific case. In fact, many other parameters lead to the necessary application of complex orders. The complexity of balancing order standardization is illustrated by [28] and [10], both from the point of view of TSOs within a central dispatch system (in Greece for the former article, in Italy for the latter). Indeed, with a central-dispatch system, it is the role of the TSO to create market orders for BSPs in its area, based on the operating constraints and the generation plan communicated to him. Notably, the first article looks at RR products, and shows how precise ramping constraints can conflict with order standardization.

To deal with these constraints, market actors can adjust the divisibility of their market orders and use several types of coupling links between them (cf. rows "Order divisibility" and "Coupling links permitted" in Table 1).

2.4 Integration of operating constraints in academic models and studies

A detailed review of how operating constraints are taken into account in models simulating electricity markets (and in particular balancing markets) was conducted, including the following models: MASCEM [41], PowerACE ([11] and [12]), AMIRIS [38], EDisOn ([7] and [5]), EMPS [20], COMPETES [19], PRIMES-IEM [21], OPTIMATE[5] [25], stELMOD [2], WILMAR [40], HiREPS [32], SiSTEM [34]. Results of this review are exposed in Table 2.

[5]OPTIMATE is the precursor of the ATLAS model used in this study.

Model	Reference article and authors	Maximum power	Minimum power	Maximum ramping	Minimum time ON	Minimum time OFF	Startup duration	Shutdown duration	Minimum stable power duration	Notice delay
AMIRIS	Reeg et. al.: *AMIRIS: An Agent-Based Simulation Model for the Analysis of Different Support Schemes and Their Effects on Actors Involved in the Integration of Renewable Energies into Energy Markets*	✓	✓							
flexABLE	Qussous et. al.: *Increasing the realism of electricity market modeling through market interrelations*	✓	✓							
powerACE	Fraunholz, Keles, Fichtner: *On the role of electricity storage in capacity remuneration mechanisms* Fraunholz, Kraft, Keles, Fichtner: *Advanced price forecasting in agent-based electricity market simulation*	✓	✓							
ElbaABM	Poplavskaya, Lago, Stromer & de Vries: *Making the most of short-term flexibility in the balancing market: Opportunities and challenges of voluntary bids in the new balancing market design*	✓	✓							
EMPS	Jaehnhert & Doorman: *Modelling An Integrated Northern European Regulating Power Market Based On A Common Day-Ahead Market*	✓	✓							
GAPEX	Cincotti & Gallo: *GAPEX: An Agent-based Framework for Power Exchange Modeling and Simulation*	✓	✓							
EDisOn	Dallinger, Auer, Lettner: *Impact of harmonised common balancing capacity procurement in selected Central European electricity balancing markets* Burgholzer: *Evaluation of different balancing market designs with the EDisOn+Balancing model*	✓	✓	✓						
MASCEM	Vale et. al.: *MASCEM: Electricity Markets Simulation with Strategic Agents*	✓	✓	✓	✓					
HiREPS	Ortner: *The future relevance of electricity balancing markets in Europe - A 2030 case study*	✓	✓		✓	✓				
PRIMES-IEM	Kannavou, Zampara & Capros: *Modelling the EU Internal Electricity Market: The PRIMES-IEM Model*	✓	✓	✓	✓	✓				
COMPETES	van Hout, Koutstaal, Ozdemir & Seebregts: *Quantifying flexibility markets*	✓	✓	✓	✓	✓				
stELMOD	Abrell & Kunz: *Integrating Intermittent Renewable Wind Generation - A Stochastic Multi-Market Electricity Model for the European Electricity Market*	✓	✓	✓	✓	✓				
WILMAR	Tuohy, Meibom, Denny, O'Malley: *Unit Commitment for Systems With Significant Wind Penetration*	✓	✓	✓	✓	✓	✓			
AMES	Tesfatsion & Battula: *Analytical SCUC/SCED optimization formulation for AMES V5.0* Battula, Tesfatsion & McDermott: *A Test System for ERCOT Market Design Studies: Development and Application*	✓	✓	✓	✓	✓	✓	✓		
OPTIMATE	Maenhoudt & Deconinck: *Strategic Offering to Maximize Day-Ahead Profit by Hedging Against an Infeasible Market Clearing Result*	✓	✓	✓	✓	✓	✓	✓		
SiSTEM	Petitet et. al.: *Impact of gate closure time on the efficiency of power systems balancing*	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2: Operating constraints on thermal assets modeled in electricity markets studies

As illustrated in the previous figure, models used in the literature only consider a subset of all operating constraints. In particular, startup/shutdown duration, minimum stable power duration and notice delay are almost always left out. The only notable exception to these observations is the SiSTEM model, used in articles [34] and [33], which is only missing the PHS transition duration from the list of constraints established before. However, this model is constructed to represent a single market area, and therefore is unable to simulate European common markets that require by definition multiple areas.

III BALANCING MARKET INTEGRATION WITHIN THE ATLAS ELECTRICITY MARKET MODEL

In order to assess the full impact of the inclusion of operating constraints, it was important to properly represent balancing processes. To that end, a model able to simulate both cross-border balancing markets and local balancing processes was developed and integrated with the existing agent-based model ATLAS.

The ATLAS (for Agent-based short-Term eLectricity mArkets Simulation) electricity market model consists of a structured representation of a power system, and of a series of modules that model day-ahead, intraday and balancing (both RR and MFRR) markets by following the process of actual electricity markets. It was previously used to simulate day-ahead and intraday markets in the European project OSMOSE [4], and to study the interaction between balancing markets and real-time network constraints in [15]. To keep the description relatively concise, the current section only highlights the key concepts of the balancing stage modules, that were entirely developed for this study (except for the Clearing, presented in Section 3.2). A complete description of these modules, as well as all other modules of ATLAS, can be found in a two parts documentation in [24] and [6].

A specificity of balancing energy markets is that they involve two kinds of actors that are fundamentally different from each other: BSPs and TSOs. Two distinct modules are consequently used to formulate both types of orders. The resulting structure of the balancing stage of ATLAS is illustrated in figure 3.

Figure 3: Macro overview of ATLAS balancing stage modules

The following notations will be used throughout this article (Table 3):

Notation	Description
Sets	
CA	Set of all control areas
Z	Set of all market areas
U	Set of all units
U^i	Set of all units of type $i \in [g, l, th, h, st, w, pv]$. ($g$ = generation, l = load, th = thermal, h = hydro, st = storage, w = wind, pv = photovoltaic)
O	Set of all market orders
O^{up}	Set of all upward market orders
O^{down}	Set of all downward market orders
C^{excl}	Set of all coupling instances of type $Exclusion$
C^{pc}	Set of all coupling instances of type $ParentChildren$
C^{idr}	Set of all coupling instances of type $IdenticalRatio$
Temporal parameters	
t_m^{ex}	Execution date of the market m.
t^{start}	Start date of the effective period of the market.
t^{end}	End date of the effective period of the market.
Δt_m	Time step of the market m (in min)
T_m	Effective time frame of the market m, i.e. $T_m = [t_m^{start}, t_m^{start} + \Delta t_m, \dots, t_m^{end} - \Delta t_m]$
T_{id}	Time frame of the combinatorial index id.
Decision variables	
$\delta_{u,t}^{turned\_on}$	Binary variable indicating if unit $u \in U^{th}$ is starting at $t \in T_m$
$\delta_{u,t}^{turned\_off}$	Binary variable indicating if unit $u \in U^{th}$ is shutting down at $t \in T_m$
$Q_{u,id}^{ResDir,max}$	Maximum quantity in direction $ResDir \in [up, down]$ that can be offered on unit u, for the combinatorial index id
$Q_{u,id}^{ResDir,min}$	Minimum quantity in direction $ResDir \in [up, down]$ that can be offered on unit u, for the combinatorial index id
Unit characteristics and input data	
$P_{u,t,t_m^{ex}}^{plan}$	Power output (in MW) of unit $u \in U$ at time $t \in T_m$, seen from time t_m^{ex}
$P_{u,t}^{max}$	Maximum power output (in MW) of unit $u \in U$ at time $t \in T_m$
$P_{u,t}^{min}$	Minimum power output (in MW) of unit $u \in U$ at time $t \in T_m$
$P_{u,t,t_m^{ex}}^{for}$	Forecast of the maximum power output (in MW) of unit $u \in [U^w, U^{pv}, U^l]$ at time $t \in T_m$
c_u^{var}	Variable cost (in €/MWh) of unit $u \in U$
c_u^{SU}	Startup cost (in €) of unit $u \in U$
$Res_{ut,t_m^{ex}}^{ResType,ResDir}$	Procured reserves of type $ResType \in [FCR, aFRR, mFRR, RR]$ in direction $ResDir \in [up, down]$ on unit u at time t, seen from t_m^{ex}
d_u^{SU}	Startup duration (in min) of unit $u \in U^{th}$
d_u^{SD}	Shutdown duration (in min) of unit $u \in U^{th}$
d_u^{minOn}	Minimum time on duration (in min) of unit $u \in U^{th}$
d_u^{minOff}	Minimum time off duration (in min) of unit $u \in U^{th}$
$d_u^{minStable}$	Minimum stable power duration (in min) of unit $u \in U^{th}$
d_u^{notice}	Notice delay (in min) of unit $u \in U$

Table 3: General notations

3.1 Market Orders Formulation

A balancing energy market order has a set of characteristics presented in Table 4:

Notation	Description
t_o^{ex}	Creation date of order o
t_o^{start}	Start date of order o
t_o^{end}	End date of order o
q_o^{max}	Maximum quantity of power offered for order o
q_o^{min}	Minimum quantity of power offered for order o
q_o^{acc}	Accepted quantity of power offered for order o. This variable is an output of the Clearing module.
p_o	Price of order o
σ_o	Sale / Purchase indicator order o, $\sigma = 1$ for purchase, -1 for sale

Table 4: Characteristics of a balancing energy market order

In addition, market orders can be coupled with each other in several ways to represent operating constraints (c.f. Section 2.3). In ATLAS, the following coupling types are implemented:

- *Exclusion*, which indicates that the Clearing stage can accept at most one order amongst the ones that are part of the Exclusion coupling group.
- *Parent Children*, in which one order is classified as $Parent$ and the other ones as $Children$, and that forces the Clearing stage to accept the $Parent$ order if at least one of the $Children$ is accepted. It is similar to the "Multi part" coupling type indicated in Table 1.
- *Identical Ratio*, which indicates that if the Clearing accepts one order o of this coupling group at a certain acceptance ratio $r = (q_o^{max} - q_o^{acc})/(q_o^{max} - q_o^{min})$, then all other orders of this group need to be accepted with the same acceptance ratio. It is similar to the "Linked in time" coupling type of Table 1.

The slight differences in terms of names or characteristics between coupling links in ATLAS and the ones in actual RR/mFRR markets can be explained by the fact that, in ATLAS, they are used for all markets (day-ahead, intraday and balancing) and are therefore hybrids between coupling links that can be found in all of these markets.

3.1.1 BSP Orders Formulation

The goal of this module is to formulate, for each generation or load unit, balancing market orders that comply with the standards required for the target market, while accounting for a complete set of operating constraints (that depends on the unit type) and for reserves previously procured. Every unit is looked at individually to determine the upward and downward power it can offer, while taking into account the generation plan determined from prior market phases, any previously procured reserves as well as its operating constraints. The number of periods in the time frame of a balancing market is however much less than for a day-ahead or even an intraday market: 4 periods at most in the case of the RR market, whereas it goes up to 24 periods for a day-ahead market. Consequently, it is possible to directly compute the available power of every unit, even thermal units, without having to rely on an optimization problem.

Thermal units order formulation

For each unit $u \in U^{th}$, the module begins by checking if none of the key duration constraints detailed in 2.3 is longer than the time step of the market:

$$\textbf{if } \Delta t_m \geq max(d_u^{SU}, d_u^{SD}, d_u^{minOn}, d_u^{minOff}, d_u^{minStable}) \textbf{ then}$$
$$\{T_{id}\} = \{\{t_m^{start}\}, \{t_m^{start} + \Delta t_m\}, \ldots, \{t_m^{end} - \Delta t_m\}\}] \quad (1)$$
$$\textbf{else} \quad \{T_{id}\} = Combinatorial(T_m) \quad (2)$$

If this is verified, it means these constraints will not be restrictive in the order formulation process, and each time step of T_m is considered individually (Equation 1). In the other case however, duration constraints are likely to impose restrictions on orders over multiple time steps. To take that effect into account, the module identifies all available combinatorial time indexes over which an order, or a "block" order (meaning an order that lasts over several time steps) could be formulated. This set of indexes is given by the function $Combinatorial()$ (Equation 2), and is illustrated in Figure 4. In this example, spanning over 3 time steps, $Combinatorial$ would identify 6 combinatorial time indexes.

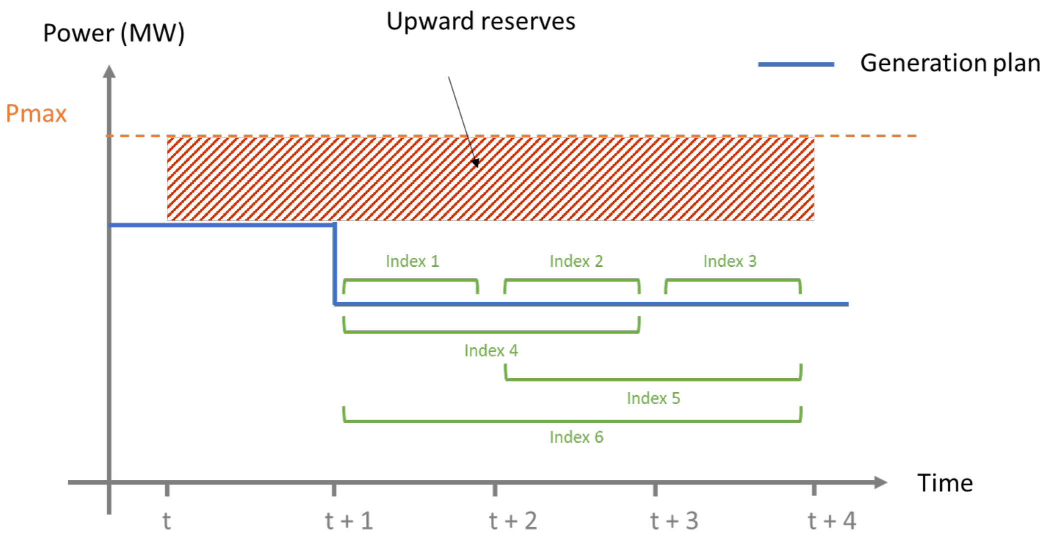


Figure 4: Definition of available time indexes

This method allows the generation of as many market orders as possible in the case of restrictive operating constraints, providing the highest possible liquidity to the market.

For each index id that was defined, the available upward power ranging between $Q_{u,id}^{up,max}$ and $Q_{u,id}^{up,min}$, and the available downward power ranging between $Q_{u,id}^{down,max}$ and $Q_{u,id}^{down,min}$ are computed, then successively updated by the steps in Algorithm 1.

Initialization of lower bounds
$Q_{u,id}^{up,min} \leftarrow 0$
$Q_{u,id}^{down,min} \leftarrow 0$
Maximum and Minimum power
$Q_{u,id}^{up,max} \leftarrow P_{u,t}^{max} - P_{u,t,t_m^{ex}}^{plan}$
$Q_{u,id}^{down,max} \leftarrow max(P_{u,t,t_m^{ex}}^{plan} - P_{u,t}^{min}, 0)$

Procured reserves
$Q_{u,id}^{up,max} \leftarrow max(Q_{u,id}^{up,max} - \sum_{type \neq RR} Res_{u,t,t_m^{ex}}^{type,up}, 0)$
$Q_{u,id}^{down,max} \leftarrow max(Q_{u,id}^{down,max} - \sum_{type \neq RR} Res_{u,t,t_m^{ex}}^{type,dn}, 0)$

Notice delay
$Q_{u,id}^{up,max} \leftarrow 0 \quad \mathit{if} \quad t - t_m^{ex} < d_u^{notice}$
$Q_{u,id}^{down,max} \leftarrow 0 \quad \mathit{if} \quad t - t_m^{ex} < d_u^{notice}$

Maximum ramping constraint
$Q_{u,id}^{up,max} \leftarrow min(Q_{u,id}^{up,max}, \Delta P_u^{max} * \Delta t_m - max(\Delta P_{t,t-1}^{plan}, \Delta P_{t+1,t}^{plan}))$
$Q_{u,id}^{down,max} \leftarrow min(Q_{u,id}^{down,max}, \Delta P_u^{max} * \Delta t_m - max(\Delta P_{t-1,t}^{plan}, \Delta P_{t,t+1}^{plan}))$

Minimum time On / Off
$Q_{u,id}^{up,max} \leftarrow MinTimeOnOff(Q_{u,id}^{up,max})$
$Q_{u,id}^{down,max} \leftarrow MinTimeOnOff(Q_{u,id}^{down,max})$

Minimum stable power
$(Q_{u,id}^{up,max}, Q_{u,id}^{up,min}) \leftarrow MinStablePower(Q_{u,id}^{up,max})$
$(Q_{u,id}^{down,max}, Q_{u,id}^{down,min}) \leftarrow MinStablePower(Q_{u,t}^{down,max})$

Startup
$\delta_{u,t}^{turned\_on} \leftarrow Startup(u,t) \quad \mathit{if} \quad P_{u,t,t_m^{ex}}^{plan} == 0$
Shutdown
$\delta_{u,t}^{turned\_off} \leftarrow Shutdown(u,t) \quad \mathit{if} \quad P_{u,t,t_m^{ex}}^{plan} > P_{u,t}^{min}$

Finalization and order formulation
$Formulate(Q_{u,t}^{up,max}, Q_{u,t}^{up,min}, \delta_{u,t}^{turned\_on})$
$Formulate(Q_{u,t}^{down,max}, Q_{u,t}^{down,min}, \delta_{u,t}^{turned\_off})$

Algorithm 1: BSPs order formulation steps

This is only an overview of how operating constraints are modeled. For length reasons, details of the implementation of functions $Startup()$, $Shutdown()$, $MinTimeOnOff()$ and $MinStablePower()$ are not displayed here, as they include several case separations. It is available in [6].

At the end of the algorithm, the function $Formulate()$ creates upward and downward market orders. Assuming that no startup or shutdown is induced by the set of orders of id (see below an explanation of these cases), the characteristics of orders of unit u are:

- Upward orders o_{up}:

$$\begin{cases} q_{o_{up}}^{max} = Q_{u,t}^{up,max} \\ q_{o_{up}}^{min} = Q_{u,t}^{up,min} \\ p_{o_{up}} = c_u^{var} \end{cases} \tag{3}$$

- Downward orders o_{dn}:

$$\begin{cases} q_{o_{dn}}^{max} = Q_{u,t}^{down,max} \\ q_{o_{dn}}^{min} = Q_{u,t}^{down,min} \\ p_{o_{dn}} = c_u^{var} \end{cases} \tag{4}$$

Startup and **Shutdown** steps may induce specific market orders. They check if a startup (resp. a shutdown) of the unit is feasible or even necessary. If so, $\delta_{u,t}^{turned\_on}$ (resp. $\delta_{u,t}^{turned\_off}$) is set to 1, and specific orders are created:

- For startup cases, an indivisible order o_{s1} is created between 0 and the minimum power of the unit, and a flexible order o_{s2} is created between the minimum and the maximum power of the unit (it is assumed to be able to reach any power output between these values when starting). Startup costs are distributed on the indivisible order, and the flexible part only takes into account variable costs. Formally, this gives the following order characteristics:

$$\begin{cases} q_{o_{s1}}^{max} = P_{u,t}^{min} \\ q_{o_{s1}}^{min} = P_{u,t}^{min} \\ p_{o_{s1}} = c_u^{var} + \frac{c_u^{SU}}{P_{u,t}^{min} * \Delta t_m / 60} \end{cases} \tag{5}$$

$$\begin{cases} q_{o_{s2}}^{max} = P_{u,t}^{max} - P_{u,t}^{min} \\ q_{o_{s2}}^{min} = 0 \\ p_{o_{s2}} = c_u^{var} \end{cases} \tag{6}$$

  A $Parent\ Children$ coupling is created between both orders, the indivisible order o_{s1} being the $Parent$ as it is required to be activated for o_{s2} to be activated as well (see Appendix A for more details).
- A similar method is applied for shutdown cases. An important note is that shutdowns can actually induce startup costs, because it forces the unit to start up again at the end of the market time frame. An indivisible order o_{s1} between 0 and the minimum power is once again created, coupled with a flexible order o_{s2}:

$$\begin{cases} q_{o_{s1}}^{max} = P_{u,t}^{min} \\ q_{o_{s1}}^{min} = P_{u,t}^{min} \\ p_{o_{s1}} = c_u^{var} + \frac{c_u^{SU}}{P_{u,t}^{min} * \Delta t_m / 60} \end{cases} \tag{7}$$

$$\begin{cases} q_{o_{s2}}^{max} = P_{u,t}^{plan} - P_{u,t}^{min} \\ q_{o_{s2}}^{min} = 0 \\ p_{o_{s2}} = c_u^{var} \end{cases} \tag{8}$$

Other coupling links between orders are also created at this stage, to represent operating constraints. They are detailed in Appendix A.

Formulation of orders for other types of units
As this study focuses on thermal units, the description of unit formulation of other types is less detailed in this article (but can be entirely found in [6]):

- Hydro units are separated into 3 different categories, being Run of River (ROR), Reservoir and Pumped Hydro Storage (PHS). ROR units are considered non-dispatchable equipment, and therefore cannot provide any reserve. PHS are modeled as Storage units, and their behavior is described in the corresponding part. Reservoir units have to comply with the following constraints: minimum and maximum power output, maximum and minimum reservoir level. Their maximum ramping capacity is assumed to be infinite.
- Storage units encompass batteries, electric vehicles and PHS. They can produce or consume energy, and follow constraints of maximum and minimum power output, maximum and minimum reservoir level, maximum ramping capacity, while having charge and discharge efficiency parameters. Specific constraints are added for electric vehicles (to take into account the energy that was used for displacement and needs to be recharged, as well as variations of the number of vehicles connected at any given time), and for PHS (the transition duration constraint evoked in 2.3).
- Wind and Photovoltaic units share the same modeling rules. A forecast of their maximum power output limits the power they can produce, and it evolves as the forecast date gets closer to real-time. In addition, their power output can be curtailed up until a threshold that can be set for each unit. These units have no maximum ramping limit.
- Flexible load is able to provide reserve as well, and is only subject to maximum and minimum power output constraints.

3.1.2 TSO Order Formulation

The second stage of the balancing markets orders formulation is the creation of TSO orders. For every time step in the market time frame, each of them computes its balancing needs $bn_{ca,t,t_m^{ex}}$, corresponding to the imbalance within the control area ca it is responsible for:

$$\forall ca \in CA, \ \forall z \in Z_{ca}, \ \forall t \in T_m, \quad bn_{ca,t,t_m^{ex}} = \sum_{u^l \in U_z^l} |P^{plan}_{u^l,t,t_m^{ex}}| - \sum_{u^g \in U_z^g} P^{plan}_{u^g,t,t_m^{ex}} \tag{9}$$

With:

- U_z^l the set of all load type units in area z.
- U_z^g the set of all generation units in area z.

This imbalance is then converted into market orders, by taking into account a restriction imposed on TSOs' orders by balancing markets: the q_o^{max} of a sell (resp. buy) order o cannot exceed the total volume of buy (resp. sell) orders emitted by BSPs in their area[6]. The price p_o of these orders can be determined by several methods, that can either be straightforward such as assigning the same price for all orders, or more refined if they aim to integrate estimates of alternative ways to compensate for this imbalance (closer-to-real-time markets, or local process still operating after balancing markets for example). In this study, the pricing method called "At all costs" is used, meaning the price of every order emitted by TSOs will be the maximum price permitted by the market (€10,000 for TERRE and MARI). Eventually, an order o^{TSO} emitted by a TSO managing the market area z at time t has the following characteristics:

$$\forall t \in T, \quad \text{if} \quad \sigma_o = 1, \quad \begin{cases} q_{o^{TSO}}^{max} = \min(bn_{ca,t,t_m^{ex}}, \ \sum_{o \in z | \sigma_o = -1} q_o^{max}) \\ q_{o^{TSO}}^{min} = 0 \\ p_o = 10000 \end{cases} \tag{10}$$

$$\forall t \in T, \quad \text{if} \quad \sigma_o = -1, \quad \begin{cases} q_{o^{TSO}}^{max} = \min(bn_{ca,t,t_m^{ex}}, \ \sum_{o \in z | \sigma_o = 1} q_o^{max}) \\ q_{o^{TSO}}^{min} = 0 \\ p_o = -10000 \end{cases} \tag{11}$$

3.2 Market Clearing

The Market Clearing stage aims to accept or reject market orders and to fix the market price, which ultimately conditions the remuneration of all involved market actors. It mimics in a simplified fashion algorithms used in real day-ahead or balancing markets (respectively EUPHEMIA[7] and TERRE[8] algorithm). The order acceptance is performed through a social welfare maximization, subject to constraints regarding transmission capacities and coupling links between market orders.

The Market Clearing algorithm was already developed in ATLAS before this study, for day-ahead and intraday markets, and is described extensively in [24]. As it was designed to be generic, it is also used for balancing markets. Its main interaction with operating constraints comes from the coupling links described in Section 3.1.1, as these links can interfere with both the order activation and the clearing price determination process.

3.3 Generation and load plans update

After receiving the results of the Clearing module, all units update their generation or load plan. In the day-ahead or intraday market, a portfolio optimization occurs here. However, given the short response time imposed by balancing markets (see Section 2.2), it is assumed that there is not enough time for this optimization. Instead, all market

[6]This is indicated in the document https://eepublicdownloads.entsoe.eu/clean-documents/events/2018/terre/20180319_TERRE_Stakeholders_presentation.pdf

[7]Complete description of the algorithm at: https://www.nordpoolgroup.com/globalassets/download-center/single-day-ahead-coupling/euphemia-public-description.pdf

[8]Updated description of the algorithm:
https://eepublicdownloads.azureedge.net/webinars/20210316_TERRE_Stakeholder_Workshop_Telco_presentation.pdf

actors respect exactly what has been activated on each unit by the Clearing module, and update their dispatch accordingly.

3.4 Balancing Mechanism

Economic or technical reasons can lead to market areas still being imbalanced after balancing markets. A last module is used to correct any remaining imbalance. It is based on the historical local process used by the French TSO RTE called ”Balancing Mechanism” (FrBM hereafter), which currently still runs after the RR market, and has been developed in ATLAS [6].

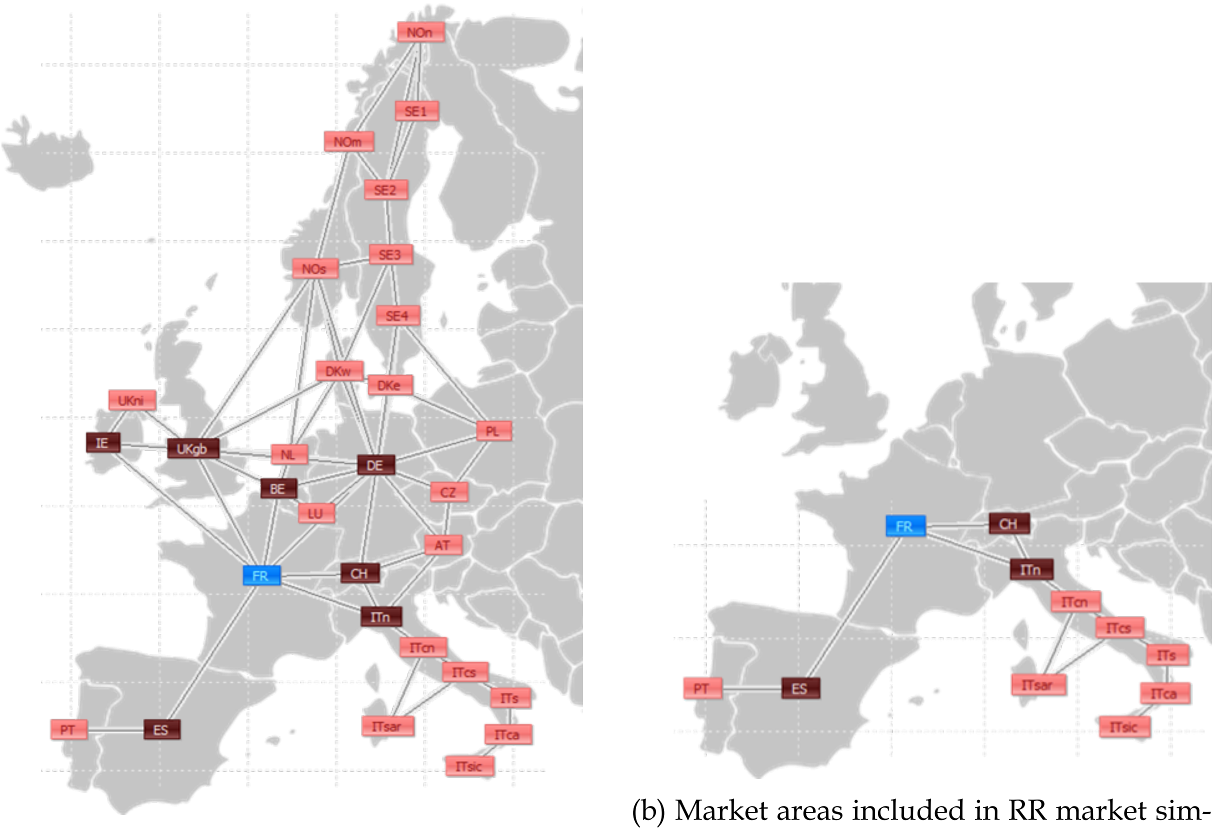
This process considers each TSO individually, along with its control area. Every unit in this area is required to communicate to its TSO its generation or load plan, alongside all of its operating constraints, and an activation price. The TSO then computes the remaining imbalance in its area, and solves an optimization to identify the units that need to be activated to correct the imbalance at the least cost, while taking into account all operating constraints. Each activated unit is then remunerated (or has to pay, if it was activated as a downward reserve) according to a pay-as-bid method.

IV METHODOLOGY

The literature review presented in Section 2.4 highlighted that the operating constraints associated with thermal generation units are only partially taken into account in the articles modeling electricity markets. To quantify the impact on market performance of this simplified view, a market simulation on a European-wide power system was performed using the ATLAS model, following a methodology described in this section.

4.1 Input data

The input dataset comes from the 2030 scenario of the Energy Pathways to 2050 study [39]. It represents the European power system in a simplified way, while capturing its local particularities by modeling it with 32 interconnected areas based on official European bidding zones, each with specific generation and consumption assets. Transmission lines and capacities are derived from the current system and from European as well as national network development plans. The resulting map is shown in Figure 5a.



(a) Complete European power system

(b) Market areas included in RR market simulations

Figure 5: Map of the European power system in the 2030 representation used in the ATLAS case study

A subset of this power system will be used for RR market simulations (Figure 5b), including all countries that are currently participating in RR markets with the exception of Czech Republic[9].

The composition of the European generating fleet, alongside installed capacities in power-to-gas (P2G) technologies, are given in Table 5. It is also detailed for each area in Appendix B (Table B.2). Most thermal units are clustered at an almost national scale (CCGT in Germany or the United Kingdom for instance), meaning that the results presented in this article are probably still underestimating the impact of operating constraints.

Storage assets stand out amongst other types of generation assets because of the following particularities:

- Batteries and PHS can withdraw energy on top of injecting it into the network, which is indicated in the table by a negative value. In the case of an identical maximum power in both directions, the sign $\pm$ is used.
- The capacity of electric vehicles connected to the network is always fluctuating, and is comprised within the ranges given for each area. In this study, electric

[9]Czech Republic is not currently not directly connected to the other participants of the RR market, and essentially consists in a local closed RR market

vehicles are assumed to be unable to function in the so-called "vehicle to grid" mode, meaning that they can only consume energy to charge (and not act as generation units).

Technology	Thermal				Hydro	Storage			Wind	Solar	P2G	Other
Sub-technology	Gas	Oil	Coal	Nuclear	/	Batteries	PHS	Electric Vehicles	/	/	/	/
Total installed capacity (GW)	229	2.6	52.7	85.7	145.5	0.5	48.5	2.8	358.9	321.5	25.5	20.5

Table 5: Synthetic view of European installed capacity of generation and P2G technologies in the input dataset

Regarding unflexible load, each area contains exactly one asset of this type. The peak load of each one over the simulated period is represented in Table B.1 of Appendix B. The only exception is the French (FR) zone, which also contains one unit of heavy electric vehicles (trucks and buses), modeled as a pure consumption asset with a capacity of 1750 MW.

Finally, all thermal units in the different areas have their own characteristics, and in particular their specific operating constraints depending on their fuel type. A qualitative overview of these values is presented in Figure 6. These mean values are adjusted with small variations for the different areas.

Unit type / Fuel type	Minimum time ON	Minimum time OFF	Startup duration	Shutdown duration	Minimum stable power duration
New CCGT	120	120	60	60	15
Old CCGT	180	180	60	60	15
OCGT	0	0	25	25	15
Conventional gas	300	300	30	30	15
New lignite	480	480	600	600	30
Old lignite	660	660	600	600	30
Coal	300	300	60	60	30
Oil	0	0	15	15	0
CHP oil / heavy oil	180	180	15	15	0
Nuclear	720	720	600	600	120
French nuclear	1440	1440	600	600	120

Table 6: Qualitative values (in minutes) of operating constraints in the input dataset

4.2 Scenarios

In order to capture the individual effects of every operating constraint on thermal units, as well as their influence when modeled together, the following 6 scenarios are studied (Table 7).

Operating constraints \ Scenario	*Minimum constraints*	*Basecase (BS)*	*BS + MinTimeOn/Off*	*BS + Startup/Shutdown*	*BS + MinStablePower*	*All constraints*
Maximumpower/ Minimum power	✓	✓	✓	✓	✓	✓
Maximum ramping	✗	✓	✓	✓	✓	✓
Minimum time ON / Minimum time OFF	✗	✗	✓	✗	✗	✓
Startup duration / Shutdown duration	✗	✗	✗	✓	✗	✓
Minimum stable power duration	✗	✗	✗	✗	✓	✓

Table 7: Scenarios simulated

A few points should be highlighted regarding these scenarios:

- When an operating constraint is described as inactive in a scenario, it means that its value is set at 0 for every thermal unit in the input data set (assuming that a maximum ramping of 0 MW/min corresponds to an infinite ramping potential).
- Minimum time ON and minimum time OFF constraints are grouped into the same scenario, as they are usually symmetrical (in the sense that the same value is chosen for both constraints) and that they are usually implemented together since they are based on the same concepts. The same logic was applied for startup duration and Shutdown duration constraints.
- The second scenario is considered as the base case, because as Table 2 showed, nearly all models include at least the Minimum power, Maximum power and maximum ramping constraints. The first scenario, referred to as *Minimum constraints*, was simulated to evaluate the impact of removing the maximum ramping constraint. Similar sensitivity scenarios could not be carried out for maximum power and minimum power constraints, as they are required for ATLAS market simulation modules to run properly.

4.3 Simulations framework

Because of computation time constraints, the entire sequence of short-term electricity markets (i.e. day-ahead, intraday, RR and mFRR markets) could not be simulated over the whole year of data. 3 days were selected because of their characteristics: an autumn day with rather standard load and renewable energy generations across all areas (Day A), a winter day stressed by high load and low photovoltaic generation (Day W), and a summer day with low load and high photovoltaic generation (Day S).

At first, a day-ahead market was simulated for each scenario, for each of these 3 days, on the complete European system depicted in Figure 5a. Results of day-ahead markets are detailed in Section V, which shows that all market indicators studied are almost identical for all scenarios. However, even minor differences in day-ahead results can lead to important variations regarding indicators observed for subsequent markets (notably market liquidity indicators). Consequently, and to better understand the impact of operating constraints on balancing markets specifically, a single day-ahead market that includes all operating constraints presented in Figure 7 was taken as the basis for balancing simulations for each day. These balancing simulations consist of 24 sequences of an RR market followed by a FrBM (one for each hour of the day), this time performed for each scenario independently and on the reduced power system presented in Figure 5b. This simulation framework is illustrated in Figure 6.

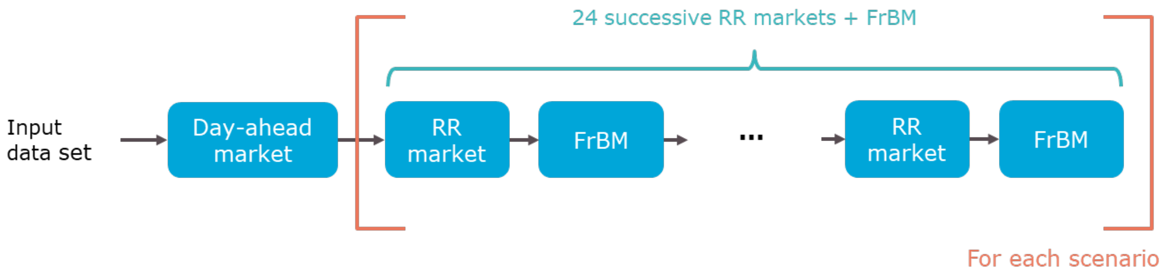


Figure 6: Simulations framework

For computation time reasons, intraday markets were not simulated here. Consequently, the imbalance seen by TSOs when formulating market orders for RR markets is greater than the one they would have computed if intraday markets were included. The following verifications were performed to make sure that this simplification does not drastically change results:

- Average balancing needs of the French TSO for products corresponding to RR reserves were estimated to be equal to 0.9 GW over 2022 in [35]. In our simulations, in the French area, the average upward (resp. downward) balancing need is equal to 1.66 GW (resp. 1.59 GW). All things considered, while greater on average, these simulated need volumes seem reasonable, especially since the power system studied is based on the projected 2030 system that incorporates more renewable energy sources than in 2022 (leading to increased balancing needs, as discussed in Section 2.1).
- There is no clear discrepancy between imbalance volumes calculated for the first RR market of the day and for the last market (meaning that TSO needs on the last RR market of the day are not substantially different, on average, from needs on the first one of the day).

V RESULTS

The results section illustrates the impacts of integrating specific operating constraints in an electricity market model on market performance, and is divided into two main categories: first a rapid overview of impacts on the day-ahead market in Section 5.1, followed by a more detailed analysis of impacts on the RR market in Section 5.2.

5.1 Day-ahead market results

The main change induced by operating constraints is the market liquidity, which consequently modifies market outcomes. Figure 7 represents the liquidity in the day-ahead market over the 3 days simulated by plotting the total volume submitted on this market (corresponding to the sum of q_o^{max} of market orders). On top of each histogram the evolution compared to the Basecase scenario is shown.

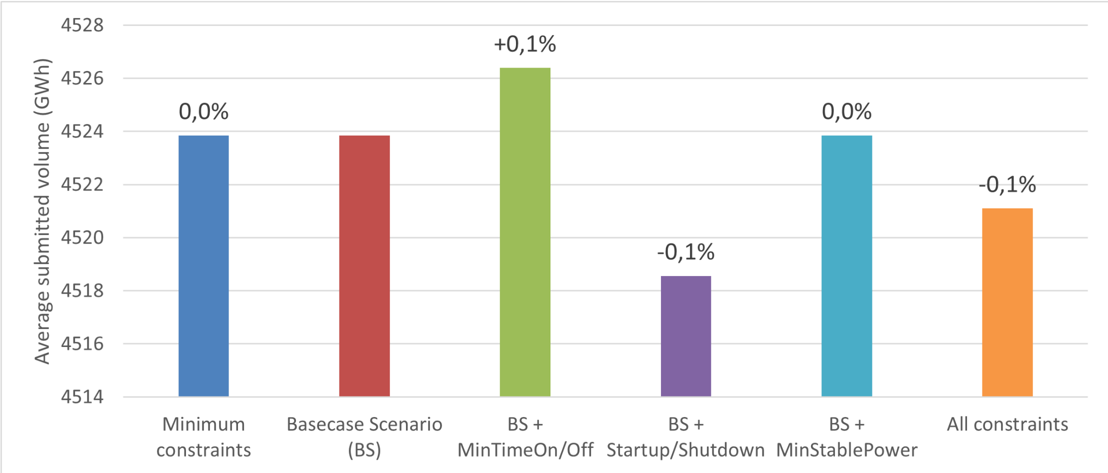


Figure 7: Total volumes offered on the day-ahead market, for each scenario

There is almost no difference in terms of market liquidity (at most a difference of 0.1% of submitted volume). The small increase observed for scenarios *BS + MinTimeOn/Off* compared to the *Basecase* can be explained by must-run situations. As Minimum Time On/Off duration can restrict a unit from shutting down for a short period and restarting after, it may be forced to offer power during this period even if its price forecast indicates that it is better for the unit not to produce. In other scenarios (except for All constraints), this situation does not exist as the unit can simply choose not to offer power on the period.

These results provide a confirmation as to why modeling advanced operating constraints in electricity markets was mostly overlooked before: while they still constrain the shape of generation plans of units, they have little impact on the volume of orders submitted, and consequently on actual performances of markets such as the day-ahead.

5.2 RR market results

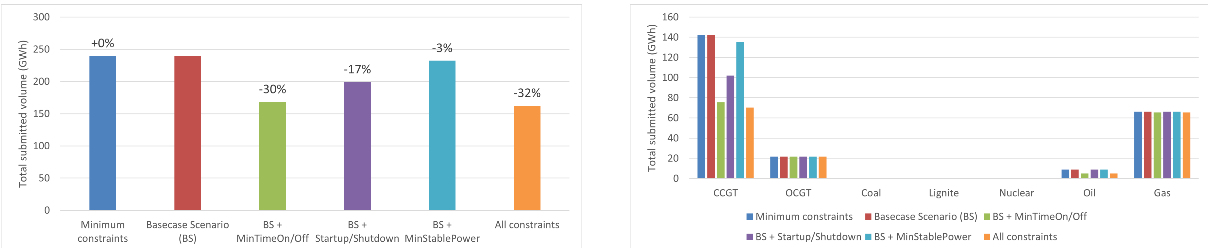
On the other hand, the RR market exhibits many more differences between the operating constraint inclusion scenarios, as the results of this section show.

5.2.1 Market liquidity

Market liquidity varies heavily with the different scenarios, as illustrated in Figure 8 and Figure 9. Upward and downward orders are differentiated, as they compensate for different types of system imbalances (a lack of downward reserves, for instance, cannot be filled by an excess of upward reserves) and therefore should not be aggregated in the same indicator. It should be noted that certain types of thermal assets are not formulating orders in a specific direction. For instance, this is the case for nuclear assets that are not making upward orders. This is not due to advanced operating constraints, but rather to the fact that they are all already producing at their maximum power output at the end of the day-ahead market. On the opposite side, oil assets are not formulating downward orders because they were not activated by the day-ahead market.

There is a significant liquidity drop between the scenarios with a simplified view of operating constraints and the others, especially the *All constraints* scenario: -32% for upward reserves, and up to -75% for downward reserves compared to the *Basecase* scenario. Here it is worth noting the relationship between specific operating constraints and unit/fuel types:

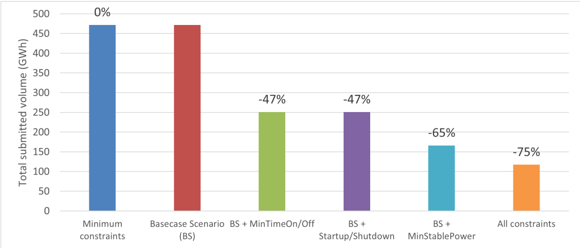
- The minimum stable power duration constraint is a prime example of this, as it is deeply associated with nuclear assets. In Figure 8b and Figure 9b, it can be seen that volumes in the scenario *BS + MinStablePower* are close to those of the *Basecase* scenario for all fuels except nuclear. In our simulations, since these assets happen to not provide upward reserves because of day-ahead market results (see previous paragraph), overall market liquidity impacts vary considerably between upward and downward reserves. Note that in the last two scenarios, a nuclear asset not functioning at its maximum power would not be able to provide upward reserves, even if the case does not arise in our simulations. Overall, this means that the minimum stable power duration constraint completely prohibits nuclear assets from participating in RR markets.
- Minimum time on/off constraints are particularly relevant for CCGT units, whose flexibility and installed capacities make them a major provider of RR reserves. If this constraint is taken into account, previously turned-off CCGT units cannot formulate orders on the RR market, as this would conflict with their minimum time on requirement. Additionally, already turned-on CCGT units cannot make shutdown orders because this would violate their minimum time off constraint.



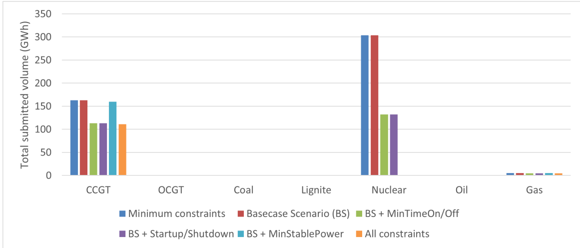
(a) Overall volume per scenario

(b) Volume per scenario, for every fuel type

Figure 8: Daily volumes of upward RR orders formulated per scenario, in GWh



(a) Overall volume per scenario



(b) Volume per scenario, for every fuel type

Figure 9: Daily volumes of downward RR orders formulated per scenario, in GWh

Day-by-day liquidity results are displayed in Appendix C. Although trends are similar, differences can still be observed between them, as the state of the power system at the end of the day-ahead market determines the range of possible RR market offers. This is particularly clear for day W (the winter day), as most CCGT units are already turned on in the day-ahead market to meet the important winter demand. Consequently, their capabilities on the RR market are much less impacted by minimum time on/off constraints, resulting in smaller differences between scenarios.

A graph showing differences between countries[10] is displayed in Figure 10. The average volume submitted by thermal units, as well as the separation between upward and downward orders, are plotted for scenarios *Basecase* and *All constraints*. It can be seen that impacts on liquidity differ between areas and directions, which was to be expected given the diverse generation mixes. France and Switzerland experience drastic decreases in the volume of downward orders submitted between both scenarios, mainly because of them having large installed capacity of nuclear assets. The relative importance of CCGT units in the Spanish thermal generation fleet leads to a greater decrease in upward orders formulated, compared to downward orders. Italy or Portugal are less impacted by these liquidity variations.

[10]Market areas of Italy are regrouped together, for clarity purposes.

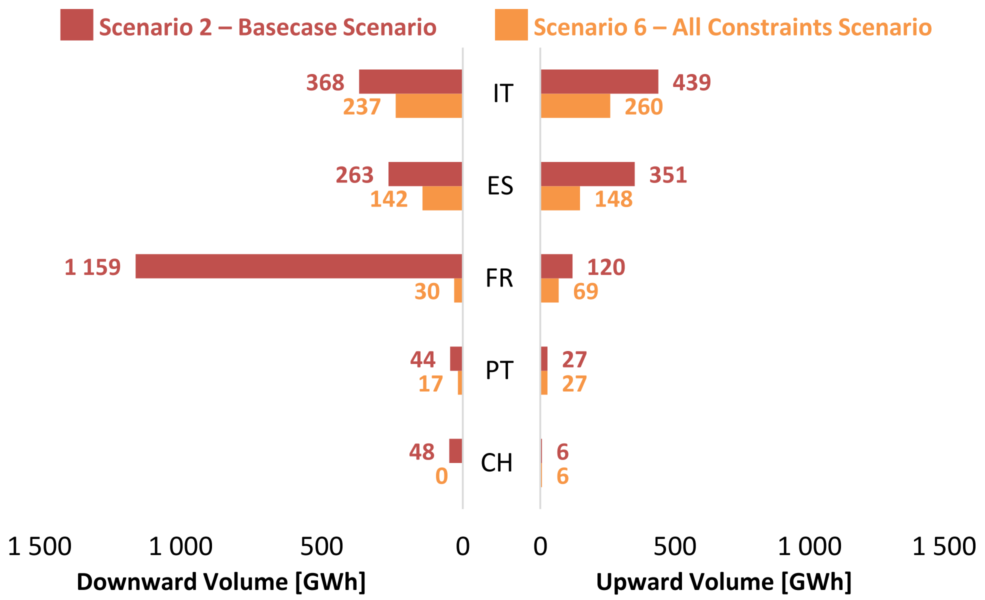


Figure 10: Volumes of RR orders submitted per country for scenarios *Basecase* and *All constraints*, in GWh

5.2.2 Impact on market outputs

The previous section demonstrated the impact of operating constraints on market liquidity, and this section studies the outcome of these liquidity variations on market results, based on 3 indicators: security of supply, TSO balancing costs and social welfare.

Security of supply
First, an important outcome of markets is the security of supply, evaluated in this study through the volume of TSO balancing demands that are not supplied by the market. This indicator is linked with the limitation imposed by the RR design on the maximum demand that can be submitted by TSOs, explained in Section 2.2: in nominal state, they cannot exceed the volume of reserves offered by BSPs in their area. If the latter is not sufficient in a given area, the associated TSO may not be able to ask its entire balancing needs on the market. The daily mean volume of unsupplied (i.e. unsubmitted) need of all TSOs is shown, for each scenario, in Figure 11.

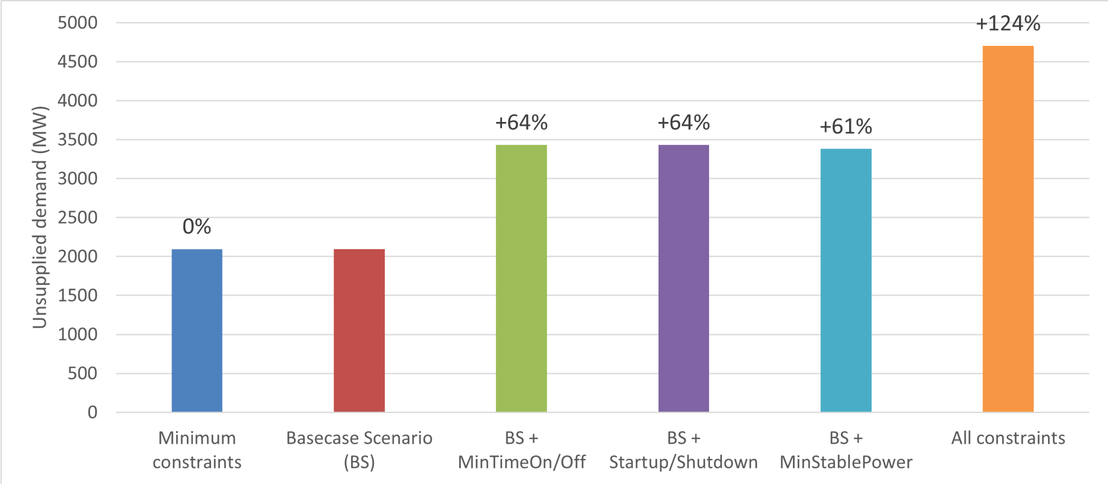


Figure 11: Volume of unsupplied TSO demands, per scenario

Compared to the *Basecase*, scenarios with additional constraints lead to a considerable increase of unmet TSO demands, around 120% more for the *All constraints* scenario. This result should be taken in a qualitative way rather than quantitative, since in our case study TSOs did not procure RR reserves in advance and only rely on the energy activation stage. It mainly advocates for the importance of the reserve procurement process: because of operating constraints and the associated liquidity decrease, the balancing energy market may not be able to provide all the balancing needs required without prior procurement.

TSO balancing costs
In addition, we looked at the overall balancing costs of TSOs c^{TSO} for each scenario, which is the sum of two components: their costs or benefits coming from the RR market, as well as the cost of resolving any remaining imbalance after each RR market using the FrBM (noted c^{FrBM}_{t,TSO_i} hereafter, for the TSO associated with market area i). The RR market component is further subdivided into two parts: the revenue coming from accepted orders, and benefits associated with congestion rents[11]

$$c^{TSO} = \sum_{t} \sum_{i \in Z} \left[\sum_{o \in O^{TSO}_{i,t}} q^{acc}_{o} * \sigma_{o} * \lambda_{t,i} - \sum_{mb_{i,j} \,|\, j \in Z} (\lambda_{t,i} - \lambda_{t,j}) * (\Delta q)^{mb_{i,j}}_{t} \right] * \frac{\Delta t_m}{60} + c^{FrBM}_{t,TSO_i} \quad (12)$$

Where:

- Z is the set of all market areas.
- $O^{TSO}_{i,t}$ is the set of all TSO orders on area i at time t.
- $\lambda_{t,i}$ is the market clearing price at time t in area i.
- $mb_{i,j}$ is the market border between areas i and j.
- $(\Delta q)^{mb_{i,j}}_{t}$ is the power flow in market border mb_{ij} (from i to j) at time t.

[11]Congestion rents are generated when a transmission line (also called a market border) between two market areas is saturated by market activations.

Average TSO balancing costs over the 3 days, for all scenarios, are indicated in the second column of each graph of Figure 13 (as part of the social welfare computation). We can observe that average costs are always higher for scenarios including more operating constraints than the *Basecase* scenario. In particular, there is a significant increase of 114% in balancing costs between scenario *Basecase* (average of 2.26 M€) and scenario *All Constraints* (average of 4.85 M€).

Furthermore, Figure 12 plots the evolution of balancing costs for each day of each scenario, compared to the same day of scenario *Basecase*. Despite the differences between simulated days that were discussed in Section 4.3, the pattern of balancing cost increase is similar across all days, which reinforces our trust in the observed consequence of including operating constraints. The scale of this increase still depends on the day, with Day A (the autumn day) displaying the largest for all scenarios.

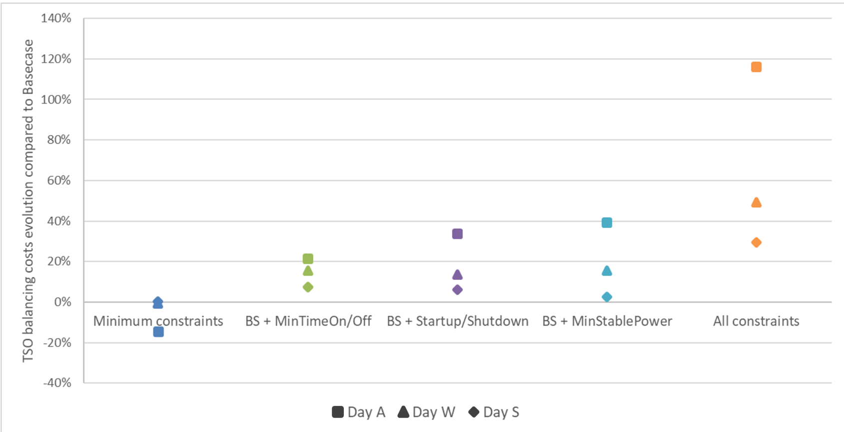


Figure 12: TSO balancing costs evolution compared to *Basecase* scenario for all 3 days simulated

Social welfare

Finally, we computed the social welfare for each scenario. On electricity markets, the classic definition of social welfare is composed of two parts ([46]): (i) the order surplus that represents the difference between the amount that the actor was willing to pay/receive and its actual payment/benefits, (ii) the congestion rents received by TSOs. This is given in Equation 13:

$$SW = \frac{\Delta t_m}{60} * \sum_{t} \sum_{i \in Z} \left[\sum_{o \in O_{i,t}} q_o^{acc} * (-\sigma_o) * (p_o - \lambda_{t,i}) + \sum_{mb_{i,j} \mid j \in Z} (\lambda_{t,i} - \lambda_{t,j}) * (\Delta q)_t^{mb_{i,j}} \right] \quad (13)$$

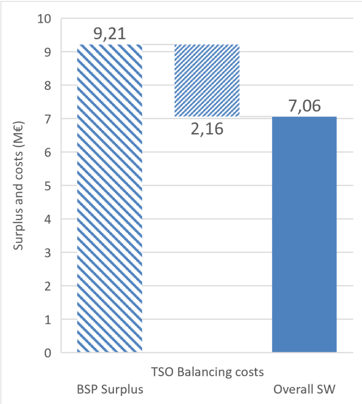
However, this definition is not appropriate for this study, as TSO orders are assumed to be formulated at all costs (i.e. at $p_o = \pm 10,000$€/MWh). If it was applied, the TSO orders surplus term $\sum_{o \in O_{i,t}^{TSO}} q_o^{acc} * (-\sigma_o) * (p_o - \lambda_{t,i})$ would lead to enormous inflation of the indicator, given that market prices λ are comprised between 50 €/MWh and 100 €/MWh in our simulations. Instead, we used the social welfare computation of

Equation 14, which corresponds to the difference between the BSP order surplus and the TSO balancing costs previously computed.

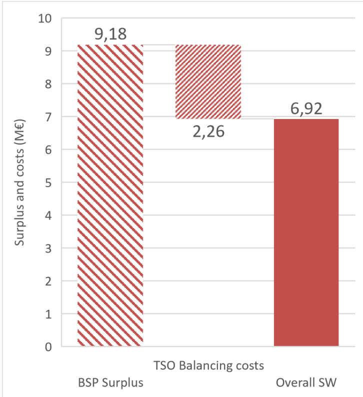
$$SW = \sum_{t \in T_{RR}} \left[\sum_{i \in Z} \sum_{o \in O_{i,t}^{BSP}} q_o^{acc} * (-\sigma_o) * (p_o - \lambda_{t,i}) * \frac{\Delta t_m}{60} \right] - c^{TSO} \tag{14}$$

Figure 13 details average social welfare results over the simulated days, including the values of both BSP and TSO components. As presented before, TSO balancing costs are higher for scenarios that include advanced operating constraints. The BSP surplus tends to decrease in scenarios with advanced constraints, although the BSP surplus of scenario *All constraints* is relatively close to that of scenario *Basecase*. Its evolution is harder to describe, as it is simultaneously influenced by variations in market prices and by the type of BSP orders limited by operating constraints. Indeed, if units with low production costs are prevented from participating in RR markets by these constraints, and more expensive units are activated instead, the resulting BSP surplus will decrease.

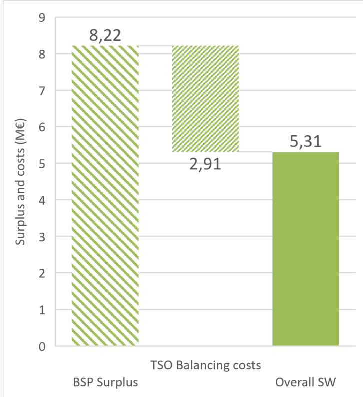
When looking at the overall social welfare however, all scenarios including advanced operating constraints induce losses of social welfare, especially the *All constraints* scenario that exhibits a decrease of around 40% compared to the *Basecase* scenario.



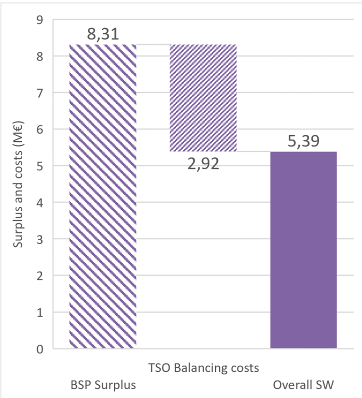
(a) *Minimum constraints*



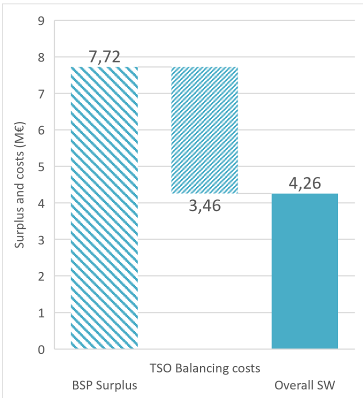
(b) *Basecase*



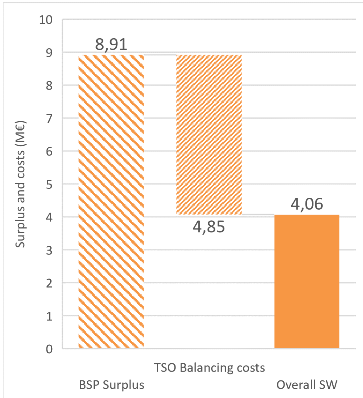
(c) *BS + MinTimeOn/Off*



(d) *BS + Startup/Shutdown*



(e) *BS + MinStablePower*



(f) *All constraints*

Figure 13: Social welfare per scenario and its decomposition, in M€

VI CONCLUSION

This article puts past studies on electricity balancing markets into perspective by focusing on the inclusion of operating constraints of thermal units in electricity markets models, with a focus on balancing markets and more specifically on the RR product. Indeed, interactions between operating constraints and strong requirements in terms of order standardization associated with the definition of RR products can lead to significant overestimation of market liquidity, and consequently of market performances.

We first compiled a list of relevant operating constraints for the time scale of balancing markets. Based on it, a literature review of the integration of operating constraints in agent-based models was conducted, and it reveals that almost all of them incorporate only a subset of this constraint list.

To address this issue, a new model of balancing markets was developed and integrated into the ATLAS agent-based model. It is then used to study the impact of such model simplifications on simulated market inputs and outputs: a day-ahead market, followed by 24 RR markets are simulated for 3 representative days from different seasons, based on 6 scenarios. Each one of them gradually introduces additional operating constraints in the simulation. Even if the intraday market was not simulated, the order of magnitude of TSO balancing needs formulated on the RR market was assessed and is quite representative.

Results of these simulations indicate that taking into account the complete set of constraints has a major impact on market liquidity, with a decrease of up to 60% of volumes of RR orders submitted by BSPs compared to the *Basecase* scenario that only includes basic constraints (maximum and minimum power, as well as ramping limit). This liquidity decrease induces several variations in market outcomes (values indicated are the comparison between the *Basecase* and *All constraints* scenarios):

- An average increase in TSO balancing costs of 114% (2.59 M€).
- An overall decrease of 40% of social welfare, taking into account the fact that TSOs formulate inelastic demands in our study.
- A reduction of the level of security of supply, illustrated by a 120% increase in the volume of TSO balancing needs that are not fulfilled by RR markets.

These effects are similar in all 3 days simulated, despite their notable differences in terms of load and renewable generation, thermic unit availability and eventually TSO balancing needs volume and direction. This reinforces our trust in the presented results. We also observed a notable link between the different constraints and the composition of the power system. In areas with a major share of CCGT units, minimum time on/off constraints are particularly influential, whereas the minimum stable power duration constraint has greater impacts on power systems with high capacities of nuclear units.

Following this study, the authors note that taking into account operating constraints, especially on thermal generation units, has a significant impact on outcomes of close-to-real-time market simulations, and should be considered when studying these types of markets in accordance with the power system modeled. It is also worth noting that this study was done on the least restrictive balancing reserve type. Indeed, mFRR markets impose heavier requirements in the standardization phase since these reserves are closer to real-time than RR, and the impact of operating constraints will be even stronger.

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APPENDICES

A APPENDIX A - COUPLING LINKS IN THE RR MARKET MODEL IN ATLAS

The creation of coupling orders by the Balancing markets BSP orders formulation stage is detailed here.

- *Identical Ratio* links are created between orders to represent a block order, i.e. one that lasts for more than one time step. This is notably used to translate the Minimum stable power duration constraint in orders, as having these links between n orders associated with the same q^{max} for all of them ensures that the unit stays at a stable power output during these n time steps.
- *Parent Children* links are created for orders inducing the startup or the shutdown of a unit $u \in U^{th}$, as explained in Section 3.1.1. A visual example is given in Figure A.1. Using such a coupling has 2 main interests. First, it ensures that the power activated by the Clearing respects the minimum power constraint, as it is forced to activate the "bottom" order entirely (as the order is indivisible) to be able to activate the "top" order. This feature could have been obtained more simply with a single order, partially divisible (with $q_o^{min} = P_{u,t}^{min}$ and $q_o^{max} = P_{u,t}^{max}$). However, properly distributing the startup cost with this simple method would not have been possible. With the *Parent Children* coupling, this fixed cost can be distributed over the relevant part, i.e. the indivisible "bottom" order.

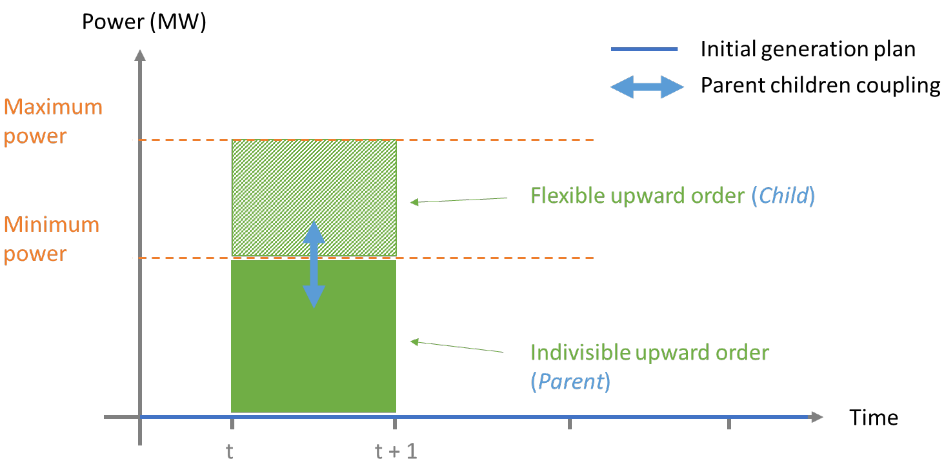


Figure A.1: *Parent Children* coupling between startup orders

- *Exclusion* links are created between consecutive orders in opposite directions. As Figure 2 shows, the real generation plan of the unit induces ramping before and after the actual start date and end date of the market order. This means that activating consecutive orders in opposite directions (upward, then downward, or the contrary) could lead to a violation of the maximum ramping constraint (Figure A.2).

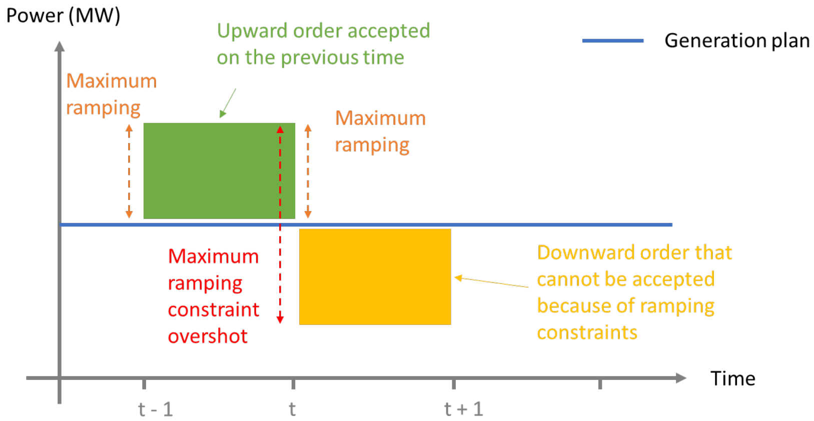


Figure A.2: Possible maximum ramping issue induced by consecutive orders of opposite direction

- Finally, *Exclusion* links are created between overlapping orders of the same direction, a situation that arises in two instances: when operating constraints induce overlapping time indexes (previously illustrated in Figure 4; or when downward and shutdown orders are created on the same time step.

B APPENDIX B - DETAILED DESCRIPTION OF INSTALLED CAPACITIES IN THE 2030 INPUT DATASET

Table B.1 indicates the peak load in each area, for all simulated days (see Section 4.3 for more details).

Area	AT	BE	CH	CZ	DE	DKe	DKw	ES	FR	IE
Day A peak load	8227	10479	5343	7851	63231	1661	3034	34305	56221	5051
Day W peak load	13723	14290	11669	12157	96320	2811	5317	44148	93729	7026
Day S peak load	10744	12353	6176	9163	77023	2047	3810	39566	69068	5477

Area	ITca	ITcn	ITcs	ITn	ITs	ITsar	ITsic	LU	NL	NOm
Day A peak load	841	3908	7446	23107	3354	1308	2731	1161	12845	3164
Day W peak load	1053	4575	9143	29692	3968	1595	3270	1548	21185	5579
Day S peak load	1088	5110	9693	29425	4153	1696	3481	1314	15922	3383

Area	NOn	NOs	PL	PT	SE1	SE2	SE3	SE4	UKgb	UKni
Day A peak load	2455	11455	20689	7110	1179	1880	8998	2345	32657	1247
Day W peak load	4220	18890	29082	9043	2008	3344	15955	4162	56098	1961
Day S peak load	2582	11721	23739	9990	1314	2047	9791	2607	38729	1433

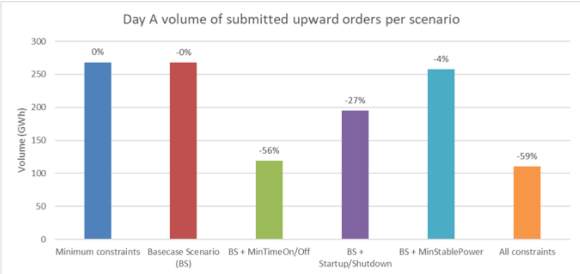
Table B.1: Peak load in each area in MW, for all simulated days

Table B.2 indicates the installed capacity in MW for each type of generation, and in brackets the number of units across which this capacity is spread (when there is more than one unit). The initial dataset contained clusters of units at national levels, especially large clusters of CCGT plants. For instance, the entire CCGT fleet of Spain was originally modeled as a single unit in ATLAS. Since this level of clusterization renders operating constraints very difficult to accurately represent, we separated the largest CCGT clusters amongst countries included in the RR simulations into smaller clusters for which the operating constraints application would be less of an approximation.

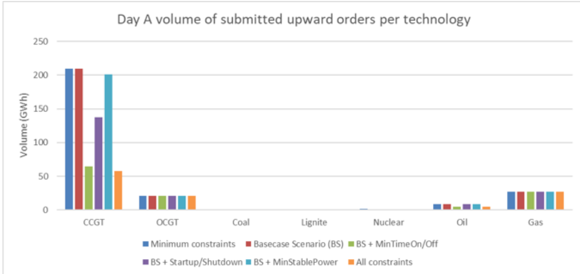
	Thermal							Hydraulic		Storage			Wind		Solar		P2G	Other non dispatchable			
Area	CCGT	OCGT	Gas other	Oil	Coal	Lignite	Nuclear	ROR	Reservoir	Batteries	PHS	Electric Vehicle	Onshore	Offshore	Photovoltaic	Thermodynamic	/	Waste	Biomass	GeoThermal	Other
AT	2824 (5)	40	1501 (2)	168	0	0	0	7800	6300	0	±3159	[21-54]	4478	0	3054	0	600	57	331	0	0
BE	6436 (3)	294	2109 (2)	158	541	0	0	100	0	0	+1395 -1237	[49-104]	4611	4253	11004	0	400	20	300	0	0
CH	0	0	660	0	0	0	2565	3800	8200	0	+3989 -3937	[26-55]	255	0	5500	0	0	0	0	0	555
CZ	1310 (4)	0	1140 (4)	14	0	4981 (2)	4055	1000	1100	0	0	[42-90]	960	0	3936	0	0	13	490	10	0
DE	18860 (3)	2932 (2)	18749 (5)	841	8968 (3)	9562 (3)	0	4200	2900	0	+7811 -7963	[231-493]	81501	21093	91300	0	5000	0	4086	0	251
DKe	39	62	110 (2)	633 (3)	1248 (4)	0	0	0	0	0	0	0	752	1963	2143	0	0	0	19	0	0
DKw	523 (4)	169 (4)	290 (2)	209	363	0	0	0	0	0	0	0	4072	3365	3151	0	0	3	71	0	0
ES	24501 (11)	0	3980 (3)	0	0	0	3041	7100	10100	0	+8465 -8275	[196-419]	48350	200	38404	7300	4000	0	0	0	1050
FR	6692 (14)	649 (2)	4197 (4)	990	0	0	59400 (4)	7400	8400	± 470	± 3800	[248-624]	33201	5200	35100	0	6500	251	377	0	775
IE	1616 (4)	446	140	324	0	78 (2)	0	400	0	0	±292	[20-44]	6000	3500	400	0	0	0	112	0	0
ITca	3283	223	20	0	0	0	0	0	0	0	±800	0	1858	300	1078	0	0	0	114	0	0
ITcn	920 (2)	142 (2)	1240	0	0	0	0	307	821	0	0	[39-83]	232	0	5125	0	0	0	75	760	0
ITcs	5625 (3)	1029 (2)	1483 (2)	0	0	0	0	380	664	0	+2538 -2518	[39-83]	3600	0	8508	0	0	0	199	0	0
ITn	22167 (13)	1019 (2)	3968 (2)	0	0	0	0	6025	7171	0	+4205 -4202	[46-99]	150	0	24185	0	0	0	867	0	0
ITs	3539 (7)	503 (2)	1590	0	0	0	0	132	1091	0	±450	0	6800	300	6346	440	1300	0	293	0	0
ITsar	590	0	300	0	0	0	0	33	161	0	+240 -242	0	2176	300	2278	0	0	0	89	0	0
ITsic	2401 (4)	646 (2)	790	866	0	0	0	23	191	0	+1158 -1254	0	3583	300	3600	440	0	0	55	0	0
LU	0	0	100	0	0	0	0	0	0	0	+1310 -1026	0	428	0	280	280	0	13	31	0	0
NL	10339 (3)	794 (2)	3770 (2)	0	3381	0	486	0	0	0	0	[65-140]	7800	13257	27150	0	3500	0	0	0	216
NOm	0	0	20	0	0	0	0	0	4931	0	±84	0	2106	0	0	0	0	0	0	0	0
NOn	0	0	200	0	0	0	0	0	5540	0	±1	0	2567	0	0	0	0	0	0	0	30
NOs	0	0	50	0	0	0	0	0	24000	0	±1030	[19-41]	3091	0	1500	0	0	35	2	0	0
PL	5001	0	6400 (4)	0	12164 (5)	7434 (3)	0	600	400	0	+1495 -1658	0	10199	3600	7737	0	700	72	914	0	431
PT	2839 (7)	0	780	0	0	0	0	1300	6700	0	+3554 -3217	[58-123]	9304	287	9383	334	2000	64	320	16	381
SE1	0	90	0	0	0	0	0	0	5315	0	0	0	5719	0	17	0	400	2	127	0	0
SE2	0	54	0	0	0	0	0	0	6795	0	0	0	6622	0	200	0	0	5	461	0	0
SE3	0	1010	0	0	0	0	6835	0	1972	0	0	[54-114]	3938	979	3005	0	0	297	1640	0	0
SE4	0	501	0	660	0	0	0	0	237	0	0	0	2581	420	1125	0	0	58	509	0	0
UKgb	34688 (4)	2128	7487 (6)	335 (2)	3984 (3)	0	9281	1900	0	0	+2744 -2684	[102-219]	15494	24826	16433	0	1100	1504	824	6	1202
UKni	1001 (2)	12	10	389	0	0	0	0	0	0	0	0	2036	317	722	0	0	19	65	0	2

Table B.2: Installed capacities in MW and number of individual units by generation type, for each area of the power system

C APPENDIX C - LIQUIDITY RESULTS FOR EACH SIMULATED DAY

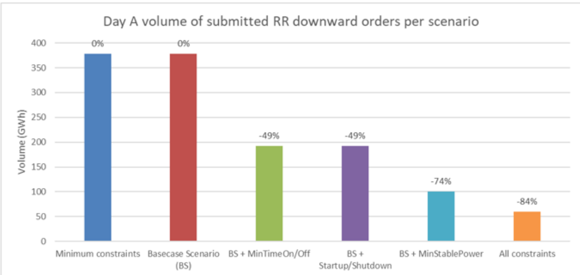


(a) Overall volume per scenario

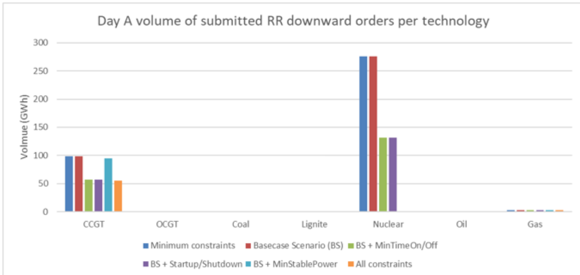


(b) Volume per scenario, for every fuel type

Figure C.1: Volumes of upward RR orders formulated per scenario for day A, in GWh

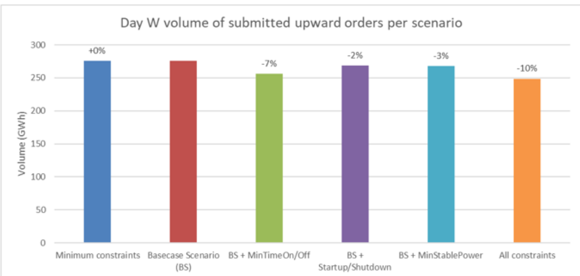


(a) Overall volume per scenario

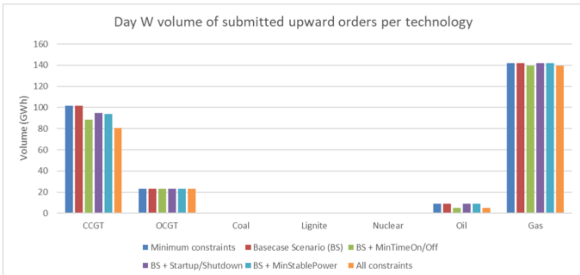


(b) Volume per scenario, for every fuel type

Figure C.2: Volumes of downward RR orders formulated per scenario for day A, in GWh

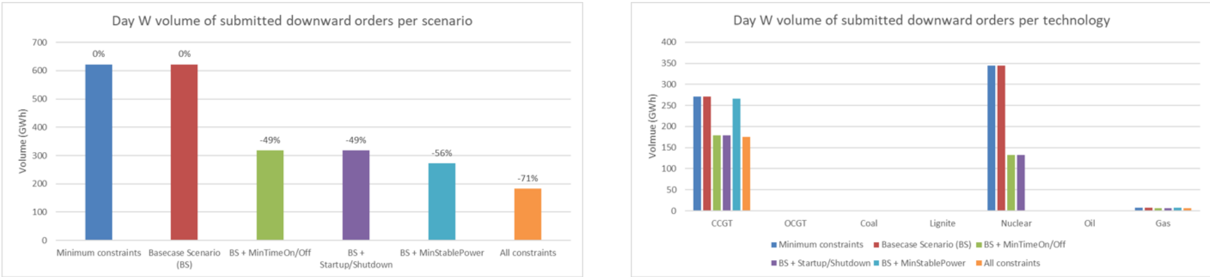


(a) Overall volume per scenario



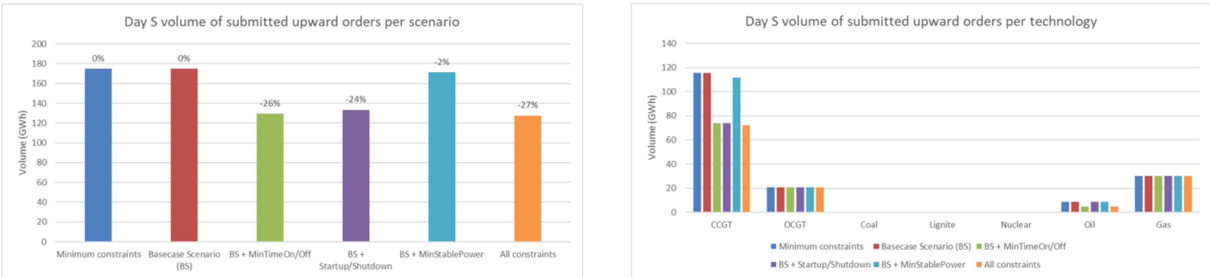
(b) Volume per scenario, for every fuel type

Figure C.3: Volumes of upward RR orders formulated per scenario for day W, in GWh



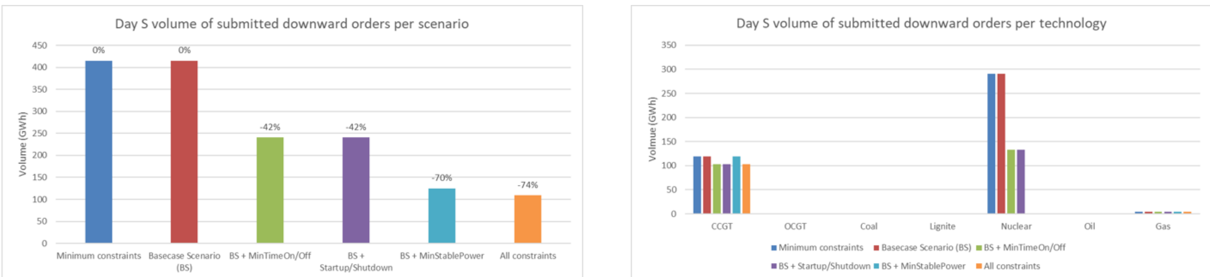
(a) Overall volume per scenario (b) Volume per scenario, for every fuel type

Figure C.4: Volumes of downward RR orders formulated per scenario for day W, in GWh



(a) Overall volume per scenario (b) Volume per scenario, for every fuel type

Figure C.5: Volumes of upward RR orders formulated per scenario for day S, in GWh



(a) Overall volume per scenario (b) Volume per scenario, for every fuel type

Figure C.6: Volumes of downward RR orders formulated per scenario for day S, in GWh