Temporal flexibility options in electricity market simulation models

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Executive Summary

This report covers the implementation of temporal flexibility options in TradeRES' agent-based electricity market simulations models. Within this project, the term "temporal flexibility option" was defined as *an asset or measure supporting the power system to balance electric demand and supply and compensate for their stochastic fluctuations stemming from, e.g., weather or consumer behaviour by adjusting demand and/or supply as a function over time or by reducing their forecast uncertainty*. Other reports from the same work package of TradeRES are published almost simultaneously, each focussing on another aspect of market model enhancements. These accompanying reports address sectoral flexibility, spatial flexibility, actor types, and modelling requirements for market designs.

Flexibility options covered in this report were selected with regard to a predominantly temporal characteristic, a contribution to TradeRES' assessment of market designs, and the feasibility to be implemented in at least one of the agent-based models (ABM) during the project's lifetime. The technical aspects of "Load shedding", "Load shifting", "Electricity storage", and "Real-time pricing" were selected for implementation. In addition, the following new electricity market products were selected for implementation: "Rolling market clearing", "Trading with shorter time units", and "Variable market closure lead times".

This report features three ABM, namely AMIRIS, MASCEM and RESTrade. After a short introduction for each of those models in Chapter 3, existing and newly implemented temporal flexibility aspects are described in detail. This comprises the ability to "Trade with shorter time units", which was available in all considered models before the start of the project. Representations of further temporal flexibility options like

- Load shedding,
- Electricity storage,
- Rolling market clearing,
- Real-time pricing, and
- Variable market closure lead times

were already available in some of the models. Those features were also introduced to some ABM of TradeRES not yet having those modelling capabilities. In addition, some existing implementations were enhanced during the course of the project. "Load shifting" was not implemented in any of the considered ABM models before the start of TradeRES and was now introduced to MASCEM and AMIRIS.

Not all flexibility options are implemented in each model. Instead, each model focusses on a subset of options to maximise the project's progress and distribute efforts across the different models. In this way, the project can best exploit the different capabilities of the individual models, and, due to the foreseen coupling of those models, can simultaneously provide the newly developed features and modelling enhancements to third parties.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ABM *agent-based models*
aFRR automatic frequency restoration reserve
ALBidS *Adaptive Learning for strategic Bidding System*
AMIRIS *Agent-based Market model for the Investigation of Renewable and Integrated energy Systems*

BES *battery energy storage*
BM *balancing market*
BRP *Balance Responsible Party*

DyLR *Dynamic Line Rating*
DOD *Depth of Discharge*
DSO *Distribution System Operator*

GFS *Global Forecast System*

FAME *Framework for distributed Agent-based Modelling of Energy systems*

HEMS *home energy management system*

IBC *initial and boundary conditions*

JADE *Java Agent Development Framework*

MASCEM *Multi-Agent System for Competitive Electricity Markets*
mFRR *manual Ffrequency Restoration Reserve*

NWP *numerical weather prediction*

SLR *seasonal line rating*

TCS *Trade, commerce and services*
TSO *transmission system operator*

VOLL *value of lost load*
vRES *variable renewable energy sources*

1. Introduction

TradeRES seeks to find market designs for a ~100% renewable energy sources electricity system. Such a system will be characterized by large fluctuations of generation from variable renewable energy sources (vRES), thus demanding for a high amount of flexibility and fast reactions of system elements to balance out these fluctuations, both in spatial and temporal terms [1, pp. 1-4, 2]. As the energy transition is progressing, the need for cross-sectoral flexibility also becomes obvious [3, p. 11491, 4, p. 1161, 5]. In this deliverable, we focus on the representation of temporal flexibility options in the electricity market simulation models. We refer to two aspects: a) technological solutions (e.g. storage systems) that can provide flexibility to electricity markets by shifting production or demand on the time axis, and b) changes in the design of markets or products that reduce the need for flexibility at the electricity markets (e.g. shorter gate closure lead times).

In this report, we provide a short overview and distinction of the temporal flexibility options considered, and explain in detail how these are implemented in the agent-based models (ABM) AMIRIS [6], MASCEM [7] and RESTrade [8]. Those models are designed to cover time-scales from hours to several years. The fourth ABM within the TradeRES project, EMLab-Generation [9, 10], takes a rather long-term perspective which covers several decades. It has a simple dispatch algorithm and uses a segmented load duration curve (20 segments) that allows it to have shorter run times. This approach, however, doesn't allow modelling temporal flexible resources on time-scales of hours or days, as needed to balance out fluctuations. Thus, EMLab-Generation is not included in this report.

This deliverable is accompanied by a series of other deliverables from TradeRES Work Package 4 "Development of Open-access Market Simulation Models and Tools". All of these deliverables are to be published within a timeframe of a few months. Please refer to these deliverables to gain deeper insights on their specific topics:

- Deliverable 4.2 [11] focusses on the implementation of sectoral flexibility within TradeRES models.
- Deliverable 4.3 [12] describes spatial flexibility options and their implementation in TradeRES models.
- Deliverable 4.4 [13] looks at new actor types in electricity market simulation models, starting with the given agent configurations of the ABMs.
- Deliverable 4.5 [14] covers modelling requirements for new market designs and policy options that shall be studied within TradeRES.

The remainder of this deliverable is structured as follows: Chapter 2 introduces flexibility options with a temporal aspect. It lays down which flexibility options are covered in this report, which ones have been covered in other WP4-related reports, and which ones are not considered within the TradeRES project. Chapter 3 describes implementations of temporal flexibility options within the models AMIRIS, MASCEM and RESTrade. Hereby, a distinction is made between the already implemented features that have been there before the start of TradeRES as well as new ones developed or planned to be developed within the course of the project. Readers interested in particular temporal flexibility options or implementations in one of TradeRES' ABMs may jump right to the respective section. Chapter 4 concludes this deliverable by detailing limitations and providing an outlook on further developments and activities.

2. Overview on temporal flexibility options

Many different temporal flexibility options in the context of electricity markets are discussed in the literature. Typically, they are employed to level out fluctuations from vRES (see e.g. [15, pp. 10-11] for a comprehensive overview). In the following, we first define the term of temporal flexibility in the context of this report (Section 2.1), and then provide an overview regarding the flexibility options we address (Section 0). Finally, in Section 2.3 we specify which aspects are addressed in the other reports of TradeRES Work Package 4.

2.1 Definitions

This report is part of the TradeRES Work Package 4 report series (see also Section 1). We define terms relating to flexibility options as specified in Table 1.

Table 1: Terminology within TradeRES

Term	**Explanation**
Flexibility option	Asset or measure supporting the power system to balance electric demand and supply and compensate for their stochastic fluctuations stemming from, e.g., weather or consumer behaviour…
Temporal flexibility option	… by adjusting demand and or supply as function over time or by reducing their forecast uncertainty;
Sectoral flexibility option	… by coupling the power sector to other sectors, the power grid to other grids, or electricity to other energy carriers;
Spatial flexibility option	… by connecting electricity surplus areas to electricity deficit areas;

2.2 Flexibility options covered in this report

This report focusses on temporal flexibility options in wholesale and balancing markets. Other ancillary services are not considered here, but subject of TradeRES deliverable D3.3 [16]. Most of the flexibility options relate to a short timeframe of days to hours, or even shorter time intervals. However, some flexibility is also targeted at longer time scales such as seasonal storage in order to cover longer periods of low or no wind and sun (often referred to as “Dunkelflaute” [17]). Regarding this report, we consider spatial or network restrictions only with respect to the ones given by wholesale markets and bidding zone design as of today.

Some temporal flexibility options may simultaneously relate to sectoral or spatial flexibility. Although these aspects cannot always be clearly separated[1], the examined flexibility options were categorised based on an agreement of members of the TradeRES consortium on what characteristic is most prevalent.

A two staged process was employed in the project: First, existing implementations of temporal flexibility options in the models were identified. Second, further options were selected that fulfil the following three criteria:

1. The flexibility option has a predominantly temporal characteristic,
2. contributes to TradeRES' assessment of market designs,
3. and can be implemented in at least one of the ABMs during the project.

The selected options are listed in Table 2.

Table 2: Temporal flexibility options covered in this report with a corresponding brief description as well as the model(s) to feature the flexibility option and whether this option was already included in the model (Stage 1) or was newly implemented (Stage 2)

Flexibility option	Brief description	Model (Stage)
Load shedding	Curtailing electrical loads when exceeding the value of lost load	AMIRIS (1, 2) MASCEM (2)
Electricity storage	Extraction of energy from the grid or another physical unit, storing it (chemically or otherwise) and feeding it back at a later time	AMIRIS (1) MASCEM (2)
Rolling market clearing	Not clearing spot and balancing markets once for all hours of the next day, but holding regular auctions based on a rolling time window, e.g., each one, four or six hours	AMIRIS (1) RESTrade (2)
Trade shorter time units	Not trading hourly products at spot and balancing markets, but shorter products, e.g., 15 mins or 5 mins	AMIRIS (1) MASCEM (1) RESTrade (1)
Real-time pricing	Final customer prices reflect the dynamics of wholesale markets, e.g., day-ahead.	AMIRIS (1) MASCEM (2)
Load shifting	Shifting electrical loads between different hours while keeping the overall energy demand of an actor unaffected	AMIRIS (2) MASCEM (2)
Variable market closure lead times	Shorter lead times between market closure and delivery, allowing to benefit from better forecast qualities	AMIRIS (2) MASCEM (1) RESTrade (2)

[1] E.g., electrical heat pumps couple the power and heat sectors (sectoral flexibility), but can also be used to for demand response applications (temporal flexibility). Thus, if electrical heat pumps were to be considered via a generic load-shifting model implementation, this would be covered in this report. In contrast, if electrical heat pumps were modelled as a power-to-heat conversion device the implementation would be discussed in Deliverable 4.2.

2.3 Further flexibility options not covered

As stated in the previous section, flexibility options which do not predominantly relate to temporal flexibility are not covered within this report. Please refer to Deliverable D4.2 [11] to learn about sectoral flexibility within TradeRES models, especially regarding interactions with the heat sector (power-to-heat), interactions with the transport sector (charging of electric vehicles), interactions with industrial processes, as well as with other energy carriers (via power-to-gas or power-to-liquids). Since there is yet limited coverage for sector coupling in the ABMs, the optimization models Backbone [18, 19] and COMPETES [20] cover this area of research within TradeRES. Spatial flexibility regarding, e.g., market splitting, dynamic line rating of interconnection power lines, cross-border markets, or nodal pricing is covered in report D4.3 [12].

3. Modelling capabilities and enhancements

Section 3.1 gives a very short introduction to the ABMs highlighted in this report, i.e., AMIRIS, MASCEM & RESTrade. It also provides the interested reader with further literature on these models. Section 3.2 covers existing implementations of temporal flexibility options of those models. Section 3.3 then describes in detail which model features regarding temporal flexibility and their data sets were newly implemented or are planned to be implemented within TradeRES.

3.1 Model descriptions

The agent-based simulation models AMIRIS, MASCEM and RESTrade are part of the TradeRES project. ABMs allow studying complex systems by representing them as set of interacting autonomous entities. This enables assessing how system properties emerge from the behaviour of those entities and their interactions. In reverse, the approach also allows investigating how a system affects its individual entities. It is thus a widely used approach applied to various areas of research, which is, however, still striving for standardisation (see, e.g., [21]). The agent-based nature of the TradeRES models makes them an ideal choice to analyse changes in policies and market designs and their corresponding impacts on the electricity markets. The following subsections give a very short overview of each of these model’s basic implementations, scope and capabilities.

3.1.1. AMIRIS

The **A**gent-based **M**arket model for the **I**nvestigation of **R**enewable and **I**ntegrated energy **S**ystems (AMIRIS) [6] was created at the German Aerospace Center in 2008 and has been enhanced and improved ever since. It represents an innovative approach to analyse and assess energy policy instruments and mechanisms for the market integration of renewable energies and flexibility options. For the design of such policy instruments and frameworks, it is necessary to consider the behaviour of actors under uncertainty and the resulting complex interdependencies [22, 23]. AMIRIS reflects these market dynamics and interactions for the analyses of various designs of policy frameworks [24, 25]. ABM offer an appropriate approach to this task, since modelled actors with their perceptions and actions are at the heart of this modelling technique.

Figure 1 depicts the agents modelled in AMIRIS as well as their interactions. Agents cover power plant operators, traders, marketers of flexibility, marketplaces, information services and regulators. These agents typically do not represent a single company or household but archetypes specialising in specific tasks and aspects. Thus, in order to represent functional energy systems, those agents are in constant exchange of data interacting with contracted partners covering other tasks. Such interactions are information flows, money transfers, and energy flows.

Due to this specialisation, power plant operators make production capacities available to electricity traders, but do not trade on the markets themselves. This task is covered by supply trader agents who try to maximise their own profitability, based on the forecasted available power from associated power plants. Marketplaces also have an agent representation. However, they do not pursue any objectives themselves but act as trading platforms whose mechanisms (e.g. regulations & market clearing) they implement. Demand trader agents purchase electricity and coordinate price- and time-dependent electricity demands. Agents providing flexibility try to maximise their profits through arbitrage (storage systems) or coordination of flexible loads (e.g. heat pumps or electric vehicles).

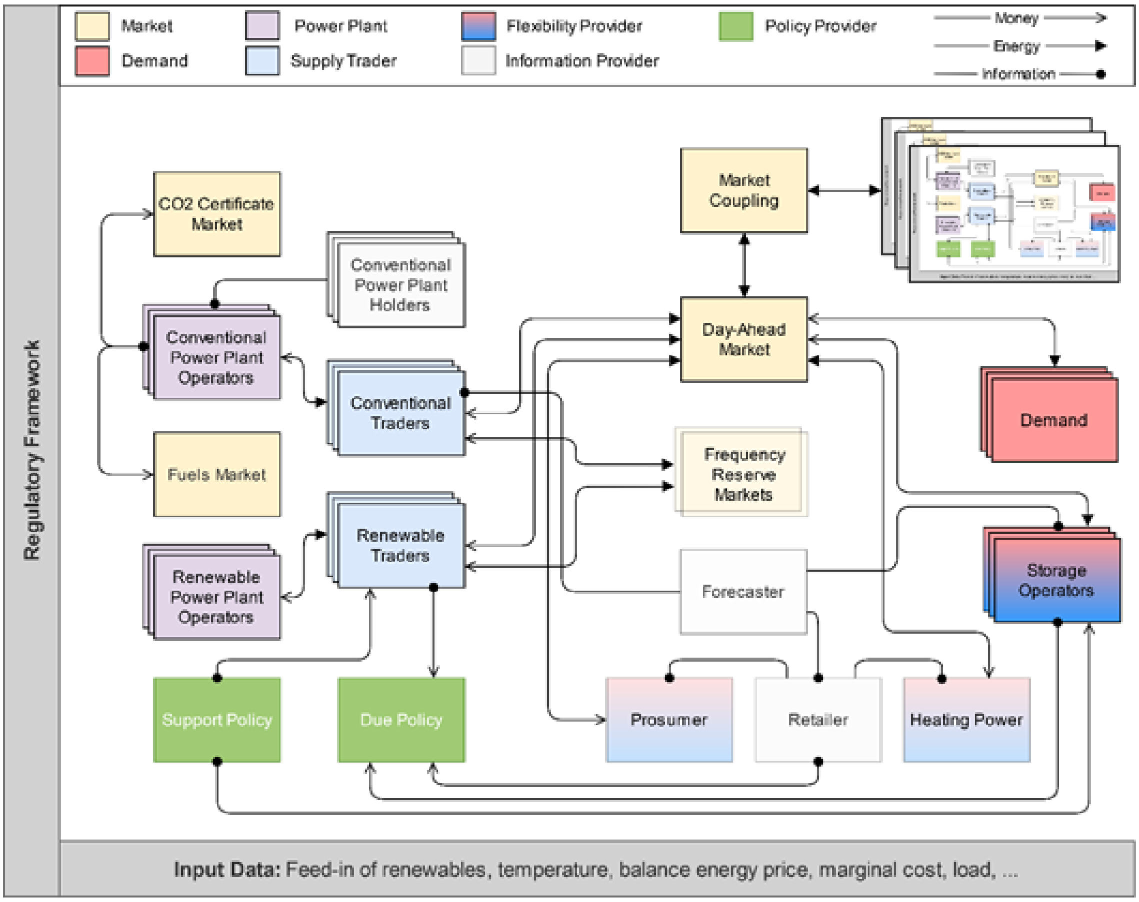

Figure 1: Basic structure of the AMIRIS model

An open-source publication of AMIRIS is currently being prepared to enhance scientific transparency and foster the exchange of models and ideas within the scientific community. Previous development steps of AMIRIS lead to the already published open Framework for distributed Agent-based Modelling of Energy systems (FAME)[2]. This software allows a rapid development of ABMs, reduces development overhead, provides a convenient model configuration tool and facilitates high-speed model execution using parallelisation. FAME models can also be deployed to high-performance computing systems with ease. Typical AMIRIS model configurations (one year at an hourly resolution) take less than a minute of computation time on a desktop personal computer. Due to its agent-based and modular nature, AMIRIS can be enhanced or modified quite easily.

3.1.2. MASCEM

MASCEM or Multi-Agent System for Competitive Electricity Markets is an electricity market simulator that was firstly introduced to the scientific community in [7]. This modelling tool allows the study of restructured electricity markets with the potential to be used by entities of very different natures and scopes of study as it is able to interact and cooperate with other multi-agent systems through the use of ontologies that manage agents' communications [26].

MASCEM was developed with the purpose of studying the complex and restructured electricity markets. It models the main involved entities and their interactions, collects data in the medium and long term to support the entities' decisions based on their characteristics and objectives and thus allows a better understanding of the regulators and market players' behaviour, the development of trade relations and the mechanisms of these markets. The simulator uses game theory, learning techniques, scenario analysis and optimization techniques for modelling and supporting market actors in their decisions.

Modelled agents correspond to various entities in the electricity market, such as: Producers, Buyers, Brokers, Virtual Power Players, Market Operators and System Operators. The user defines the market mechanisms to simulate, the number of agents as well as each agent's strategy and characteristics.

The model uses JADE[3] (Java Agent Development Framework) framework, which ensures a standard of interoperability between MASCEM and other multi-agent systems (i.e. models or components). JADE accomplishes this via a comprehensive set of services that enable communication between agents, carried out through the exchange of messages. These services include, e.g., the possibility to locate agents, to register their role and capabilities, or to support the translation and communication between different agents.

[2] https://gitlab.com/fame-framework

[3] https://jade.tilab.com/

The MASCEM simulator is additionally integrated with ALBidS (Adaptive Learning for strategic Bidding System) [27], a component for multi-agent systems equipped with adaptive learning abilities, which endows agents with capabilities to analyse negotiation contexts, such as the day of the week, the period, the particular market in which agents are negotiating, the economic situation and weather conditions. ALBidS thus allows market agents to automatically adapt their strategic behaviour according to their current situation.

3.1.3. RESTrade

The RESTrade simulator comprises i) models of traditional dispatchable and VRES power plants, ii) reserve markets and iii) Dynamic Line Rating (DyLR) of overhead power lines [28]. It supports the participation of traditional dispatchable power plants and VRES in the system balance, i.e., automatic / manual frequency restoration reserve (aFRR / mFRR) markets, according to their technical capabilities [29]. The aFRR requirements are computed considering the balancing guidelines of the ENTSO-E for the case of each country [8, 30]. Furthermore, RESTrade uses the marginal pricing theory to define the clearing-prices of these markets.

In RESTrade, the transmission system operator (TSO) is modelled as the agent with the responsibility to compute the reserve requirements of the balancing markets. It is equipped with the marginal pricing algorithms to clear each market, scheduling the dispatch of power plants based on the programmed agreements. In the case of cross-border congestion situations, which can lead to market splitting or redispatch, it also has the responsibility to compute overhead power lines capacity from long to short-run markets using a DyLR approach. Traditionally, TSOs compute the cross-border capacity using a “steady-state” seasonal line rating (SLR) of the lines. By using SLR, TSOs use conservative values of the incident wind and irradiance on the overhead lines, which normally underestimate the line capacity. The ambient temperatures can be fixed or vary seasonally and/or spatially accordingly to historical references. A DyLR methodology enables TSOs to predict and compute the maximum (temporal) capacity of the overhead lines without compromising their security. The DyLR calculation is computationally heavy, so it should be used only to avoid congestions. The DyLR methodology was implemented in Matlab. It enables TSOs to provide the transmission capacity of overhead power lines to the market according to the CIGRÉ methodology [31], which comprises a thermodynamic model of overhead power lines. In case of grid congestions in the interconnection lines, the use of a DyLR methodology enables TSOs to compute the interconnection capacities between different market zones, potentially avoiding those congestions without compromising the security of the lines [28].

3.2 Existing implementations related to temporal flexibility

The following sections describe the existing implementations of temporal flexibility options in the aforementioned ABMs of TradeRES. Since these are no new developments, the descriptions are kept concise. References to the original work enable further studies for the interested reader.

3.2.1. AMIRIS

Several flexibility options with a temporal aspect were already available in AMIRIS before the start of TradeRES, namely "Load shedding", "Electricity Storage", "Rolling market clearing", "Trading with shorter time units", and "Real-time pricing". All of these AMIRIS features are explained in the following subsections.

3.2.1.1. Load shedding

In AMIRIS, electricity prices are typically determined by intersecting a very granular supply-side merit order with an inflexible demand. For this demand, a price-independent offer at the technical price limit of the day-ahead market (currently 3,000 €/MWh [32, p. 5] is placed). See Figure 2(a) for this base case. However, load shedding can be considered by using a more granular demand curve. To do so, the overall electrical power demand is divided into distinct segments, each with individual power demand and value of lost load (VOLL) (see Figure 2(b)). In this way, an arbitrary level of granularity can also be achieved for the demand curve.

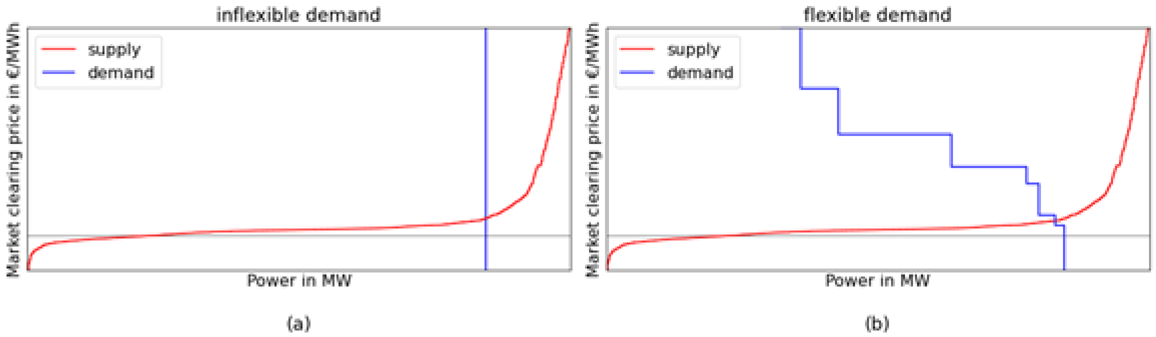

Figure 2: (a) Original inflexible demand implementation; (b) flexible structure of the demand curve

Each demand segment is associated with exogenously determined load patterns of consumers or consumer groups. In this way, the share of the individual segments from the whole electricity demand may vary for each hour. The assigned VOLL indicates the willingness to pay corresponding to the consumers of that demand segment. In general, demand segments can be flexibly determined. In [33], flexible demand options have been grouped within demand sectors using a k-means clustering approach with the interference time (time for a shift in either upwards or downwards direction), the shift time and cost values (i.e. investment expenses, variable and fixed costs) as clustering inputs parameters. The clustering resulted in two industry clusters (one mixed with processes and applications, one processes only), one cluster of household appliances, one of trade, commerce and services (TCS) applications and one mixed cluster for households and TCS containing heating and cooling appliances which is used as a default. This parameterization might change according to new scientific insights and data availability.

If power prices exceed the VOLL the demand segment is curtailed, i.e. its load shedding potential is activated to the extent needed for clearing the market. Similar to the base case with no load-shedding, a remaining inflexible demand time series is used to consider demand that must not be shed. The sum of all sheddable demand segments plus the remaining inflexible demand equals the overall demand for every hour of the simulation.

A basic load shedding mechanism was implemented to AMIRIS before the start of TradeRES. Nevertheless, several enhancements were made during the project enabling more extensive analyses regarding micro-economic potentials of load shedding. These enhancements include a comprehensive literature research to model load shedding segments building on [34] as well as the needed data processing routines. The literature research revealed high VOLL values for industrial consumers reflecting the opportunity costs from lost production (e.g. for primary aluminium electrolysis or electric arc furnaces). Especially for commercial consumers, however, only few data sets were available. Also, within TradeRES the AMIRIS model configuration was enhanced by attributing one demand trading agent with all load shedding segments. This removes the need to have one demand agent per modelled segment and reduces configurational and computational overhead.

3.2.1.2. Electricity Storage

AMIRIS features three different storage dispatch strategies:

- [MAX] Strategy to maximise profits via arbitrage trades on the day-ahead market: A single agent trades and determines the operation of its storage.
- [MULTI] Robust profit-oriented strategy for arbitrage trades on the exchange: Multiple agents trade competing with each other. Each agent has its own assigned storage.
- [MIN] Strategy for minimising system costs: A single agent trades and determines the operation of its storage.

Using the MAX strategy, the configured storage capacity is assigned to an agent that applies a strategy to maximise its profit via arbitrages on the day-ahead market. It considers the influence of its actions on the resulting price for electricity: if, for example, a significant amount of energy is stored, this increases demand and thus the price. Conversely, the price decreases when energy is sold from the storage. By considering these price sensitivities, the agent will take care to influence prices only as far as it serves its purpose to maximise the profit. Since economic incentives determine the operation of the storage facility, technical potentials may not be fully exploited. Available storage capacities may therefore not be considered in certain hours due to economic reasons.

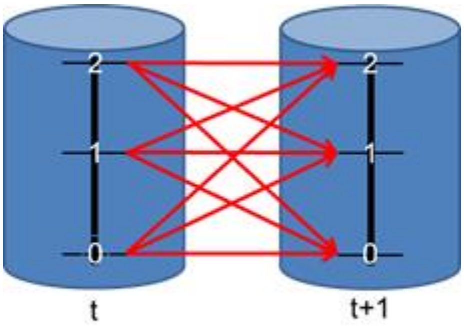

Figure 3: Schematic representation of the dynamic programming algorithm; Black steps symbolise the different available storage levels at time t and the following time step t+1. Red arrows indicate the possible storage level changes (transitions).

The MAX strategy is implemented by means of a dynamic programming algorithm (see Figure 3) [35, 36]. For this purpose, the possible energy levels are first discretised, i.e. divided into an integer number of level steps. Subsequently, the expenses or revenues that arise when proceeding to a state *j* at the next time step *t+1* are calculated for each possible initial state *i* at time *t*. The revenues and expenditures of times before *t* are also considered. Thus, an optimal sequence of storage level steps can be determined which maximises the storage operator's profits.

The MULTI strategy, like the MAX strategy, aims to maximise profits through arbitrage on the day-ahead market. In contrast to the MAX strategy, however, several agents may trade simultaneously, each controlling an individual storage facility on the market. The representation of this simultaneous trading of competing agents requires an alternative algorithm. It must be ensured that the agents pursue a strategy that allows them to maximise their profits without knowing the bids of the other agents. Therefore, the median of the forecasted electricity prices (see Figure 4) is calculated for the forecast time interval.

Based on this median electricity price during the forecast period, a minimum margin is set to account for expected charging and discharging losses and price forecast uncertainties. The median of the forecasted electricity prices is a robust measure with respect to uncertainties and errors of the price forecast. Thus, this strategy performs reasonably well when confronted with errors in the predicted prices. To determine the charging and discharging power bids the expected difference of the individual forecasted price to the price median is used. This approach neither considers the change in price due to the own charging behaviour nor the charging behaviour of other storage agents. Therefore, a continuous (hourly) adaptation of the scheduling is necessary.

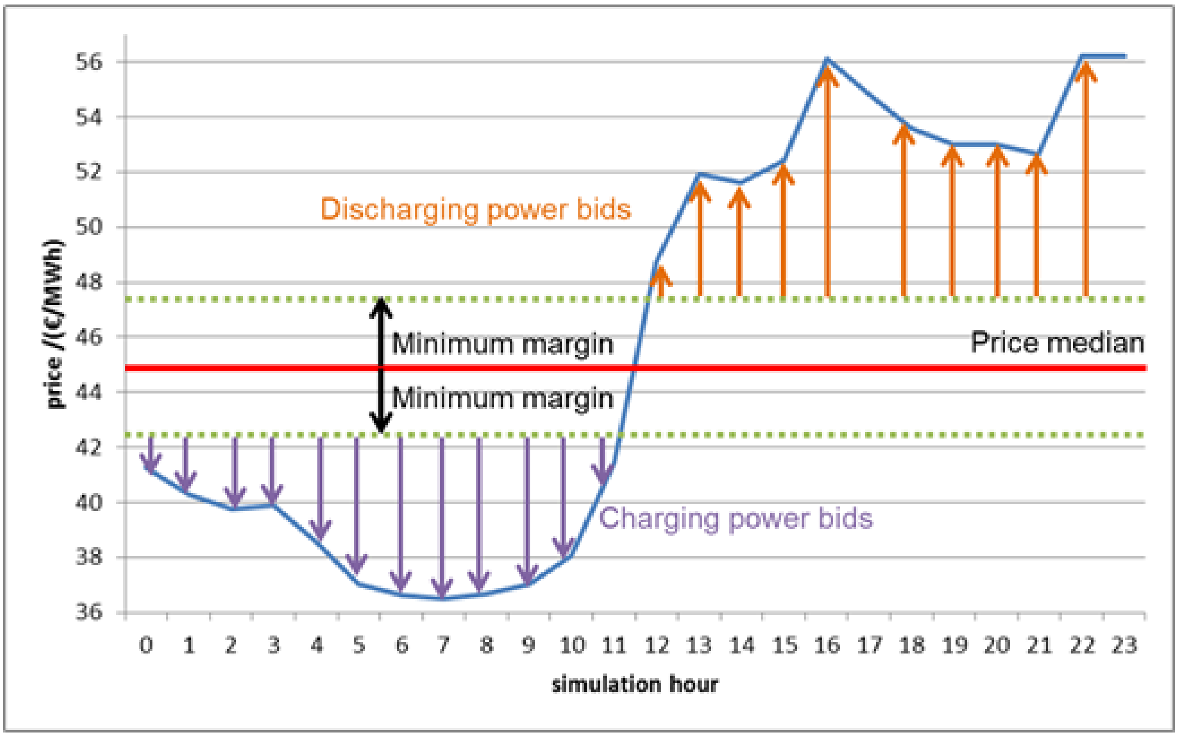

Figure 4: Schematic representation of the median-based storage strategy

The strategy MIN is implemented to compare the results of the other two strategies with a system-optimal dispatch of the storage. Its approach is similar to the MAX strategy, with only one major difference: The MIN strategy seeks to minimise the sum of system costs, i.e. the total costs for electricity generation. In this case, the storage operator agent controls the entire storage capacity and has perfect knowledge of the entire system. The agent is able to calculate the total costs of electricity generation for each hour, considering the influence of the storage dispatch. This strategy does not strictly follow the actual agent-based approach, as here the agent does not seek its own economic advantage, but optimises the overall system and has perfect foresight of all bids to be placed at the energy exchange.

3.2.1.3. Rolling market clearing

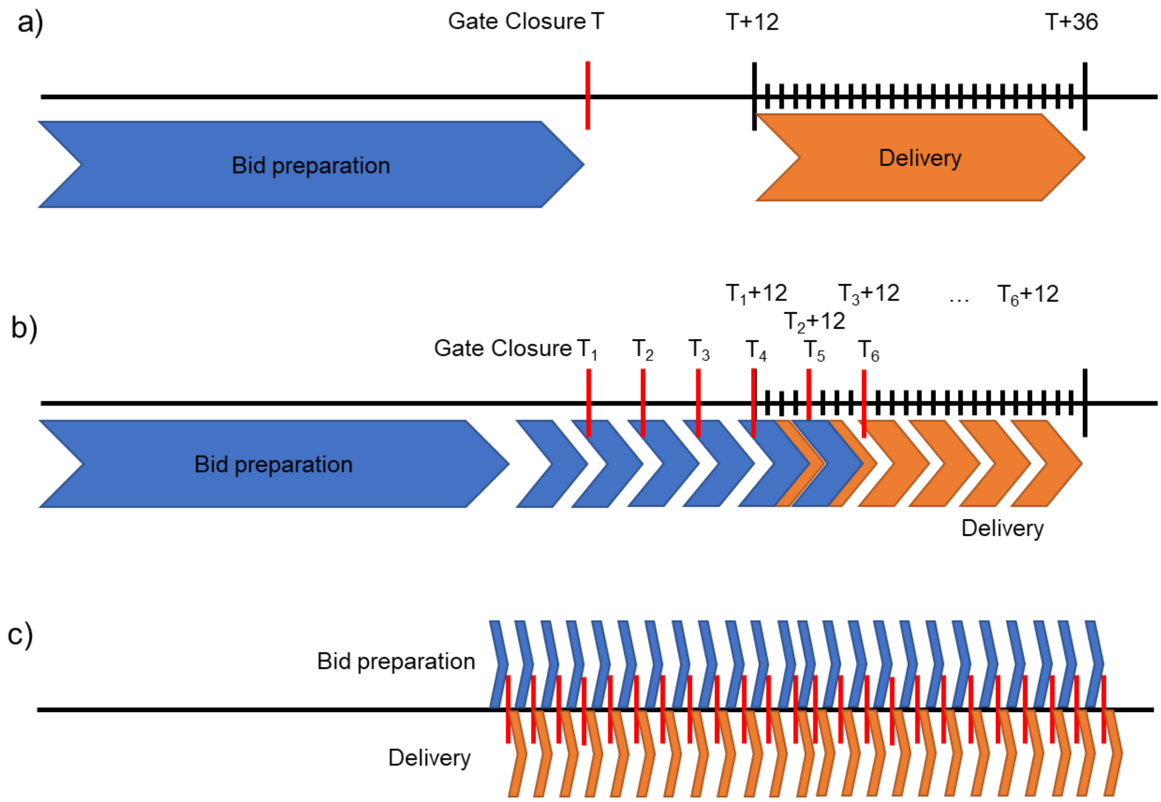

Figure 5: Schematic depiction of gate closure and delivery times for European day-ahead markets; a) current implementation, b) rolling market clearing with 6 daily intervals, c) implementation in AMIRIS

Currently, day-ahead markets are cleared for a whole day (24 individual hours) on the previous day between morning and around noon, depending on the bidding zone. Thus, the time delta between gate closure and actual delivery is not constant but varies, e.g., between 12 and 36 hours (see Figure 5a)). Once the market is closed bids can no longer be changed to include updated forecasts for later times. As a consequence, the uncertainty of prepared bids with respect to their corresponding power generation or demand is not constant but varies throughout the considered day (see also Section 3.3.1.2) – with a tendency to increase towards future hours. Rolling market clearing allows integrating forecast updates in bids for later hours of the day. Thus, it is one possibility to level-out and reduce bidding uncertainties on the day-ahead market.

Different implementations of rolling market clearing are possible, as can be seen in Figure 5b) by means of an example: There, six separate market clearings and corresponding gate closures T_n are depicted for each day, with a constant gate closure lead time of 12 hours. Each clearing, therefore, covers four-hour time intervals. This rolling horizon market clearing approach can be varied with respect to gate closure lead times and number of daily clearing intervals.

In AMIRIS, a gate closure lead time of zero with 24 daily market clearings is used by default (see Figure 5c)). Thus, delivery begins immediately after market clearing. The time unit is not fixed, so other market clearing time segment durations are also possible (see the following Section 3.2.1.4). The impact of different market closure lead times can also be considered using the method described in Section 3.3.1.2.

3.2.1.4. Trade shorter time units

At the electricity spot market EPEX, power is currently traded in hourly segments on the day-ahead market for all market zones. Intraday markets offer shorter product time units of 30 minutes or 15 minutes. AMIRIS, however, does not comprise intraday markets. Thus, to be able to model shorter time units also in AMIRIS, its agent interactions are not tightly bound to a predefined time schedule. Instead, AMIRIS follows the logic of the underlying FAME[4] framework, where each agent is programmed to react to contract signals. In this context, "contract" refers to a regular delivery of one agent to another agent. Deliveries can be anything, e.g., information, energy, or money. The time intervals of contract execution are defined in the configuration files, i.e. they are not hard-coded in the simulation. All interactions / communications of AMIRIS agents are defined via such contracts.

Since contracts can be freely configured outside of the simulation's code the interaction time intervals of AMIRIS agents can be freely adjusted. Any requested time unit for electricity products (larger than 30s) can be modelled. On the down side, agent input data is not automatically adjusted to timing changes. Thus, the time series fed to the agents need to be adapted manually since AMIRIS has no implicit data conversion routine that splits up, e.g., hourly data into shorter time slices.

We give a short example of how this feature can impact results, e.g., by changing the time resolution of an AMIRIS simulation from an hourly to a 15-minute time interval. For this purpose, all input time series (e.g. demand or vRES potentials) are scaled to that time resolution as well. We add additional fluctuations to the demand time series to demonstrate the impact of short-term variations on the electricity market. Please bear in mind that this is not a scientific evaluation of short-term effects but merely a demonstration of model capabilities.

Figure 6 shows an excerpt of a German sample for demand data time series scaled to 15-minute segments. As the vertical axis shows quarter-hourly energy demand and not power, black crosses indicate the hourly demand divided by four. Red dots show a smooth 15-minute interpolation of the hourly data such that the sum in each hour matches that of the hourly data set. Blue dashes represent the

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[4] https://gitlab.com/fame-framework

same interpolation with an added random fluctuation. The latter demand also retains the hourly sums of the demand data.

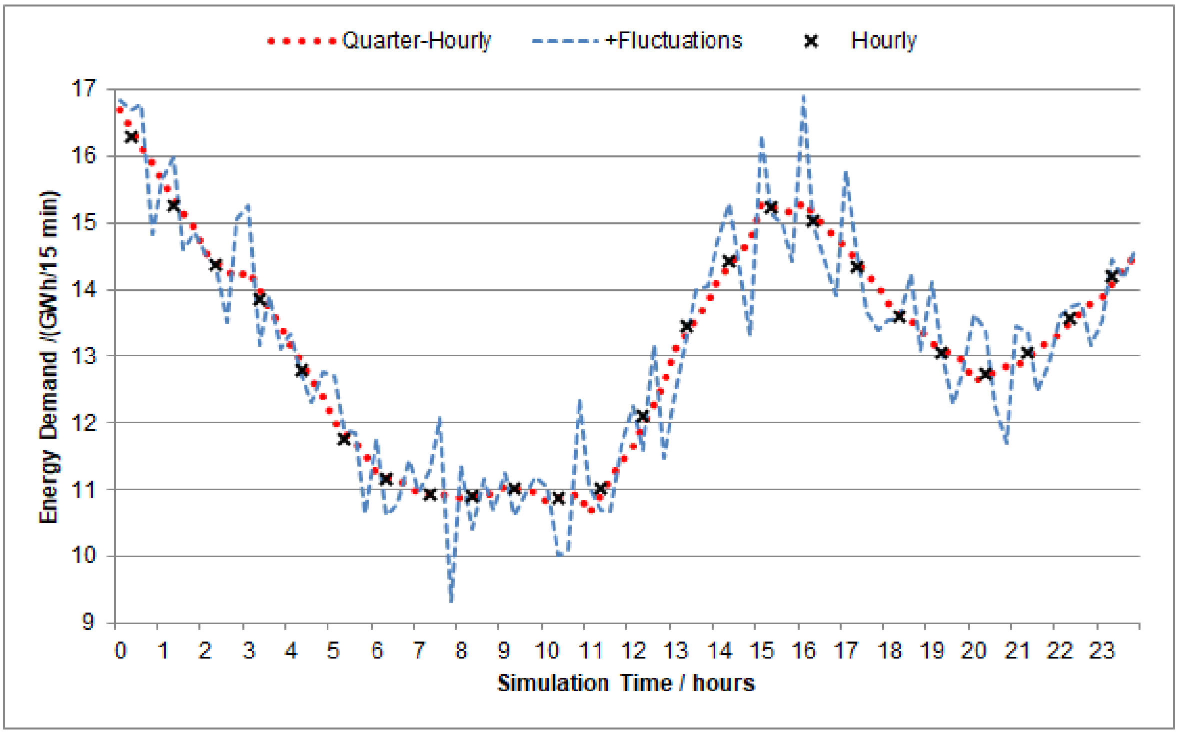

Figure 6: German energy demand over 24 hours within time segments of 15 minutes each; black crosses represent a scaled-down hourly energy demand, red dots indicate a smooth interpolation of the same data, blue dashed feature additional random fluctuations.

For the other time series, e.g., renewable feed-in potentials were smoothly interpolated without added fluctuations, but also have their hourly sums to match the corresponding original hourly values. This approach, of course, is not matching the real-world data where short-term fluctuations do occur for those time series as well. However, we ignored these fluctuations for the sake of simplicity. The result of applying these data to the electricity market in AMIRIS is shown in Figure 7. Here, the smooth demand interpolation (red dots) does not significantly change the electricity prices compared to the hourly average price (black crosses). The added random fluctuations on the demand, however, can cause strong price variations in the individual 15-minute time segments (blue dashes). Due to the non-linearity of the merit order and variations of the feed-in potentials the impact of changes in demand on corresponding prices can vary significantly. For example, in the first simulation hour, the demand deviates up to 1.5 GWh per 15 minutes from the hourly average causing a corresponding price reduction of about 5 €/MWh. At noon, however, an increase of the demand by 1.1 GWh per 15 minutes, again compared to the hourly average, causes a price jump of more than 13 €/MWh. This illustrates that finer-grained market products may have a significant impact on the revenues of market participants and electricity prices.

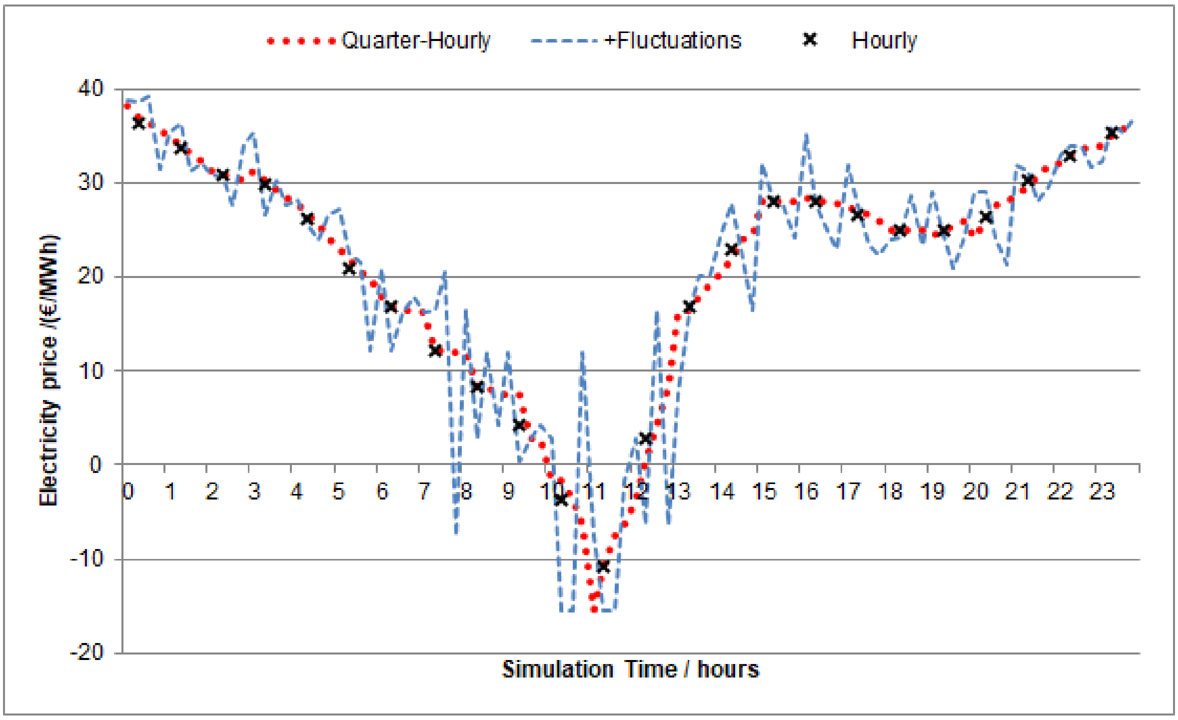

Figure 7: Electricity price over 24 hours within time segments of 15 minutes each; market and line styles corresponding to those used in Figure 6

3.2.1.5. Real-time pricing

Real-time pricing means providing final customers with prices that reflect the dynamics from wholesale markets [37, p. 15]. In AMIRIS, this is achieved by a "retailer" agent who manages end user tariff design. These include a flexible component based on the hourly wholesale market price forecast for the next day. Additional static price components are included, such as levies, taxes, or network charges. These static components, however, may outweigh the dynamic price signal and thus hamper the consumers' flexible response to real-time pricing. Therefore, currently static price components may also be designed in a dynamic way to strengthen the consumers' response to price signals.

Since in AMIRIS the retailing agent does not know the exact future price, a forecasted price is used. This forecast is obtained from an agent specialising in that task. The forecasted prices are then communicated to agents representing end-users, e.g., consumers or prosumers. An option is included to constrain the maximal and minimal price for the end-users in order to limit the price risks for both end-user and retailer agents. The retailer agent thus needs to apply markups on the end-user prices to consider potential losses from these risk transfer limitations.

It is envisaged to extend and generalize the representation of levies, taxes and other fees in AMIRIS. Capacity-related network charges, which might impact consumer behaviour as well, are also not considered yet.

3.2.2. MASCEM

The main types of negotiations supported by MASCEM are: day-ahead and intraday pool (symmetric or asymmetric, with or without complex conditions) markets, bilateral contracts and forward markets [26]. In MASCEM, it is possible to clear the market at any specified time interval; usually in periods of one hour, half-hour, 15 minutes or 5 minutes; but not excluding any other periodicity that may be defined. MASCEM market models can also be executed for any horizon before delivery, usually day-ahead, hour-ahead, 15 and 5 minutes-ahead, but any other horizons can be simulated. By selecting a combination of these market models, it is also possible to perform hybrid simulations. MASCEM supports the simulation of three of the main European electricity markets: MIBEL, EPEX and Nord Pool, reflecting the respective market rules and products. The main temporal flexibility capabilities present in MASCEM's current version relate to the possibility of defining Flexible Hourly Offers, an offer type associated to the Nord Pool market [38].

In summary, complementarily to the basis offers per negotiation period, flexible hourly orders give the opportunity to present sale offers only (purchases are not permitted), without indicating a specific period. Thus, the associated volumes can be transacted in any period of the day, depending on the offer price, and on the necessities of the market for each period.

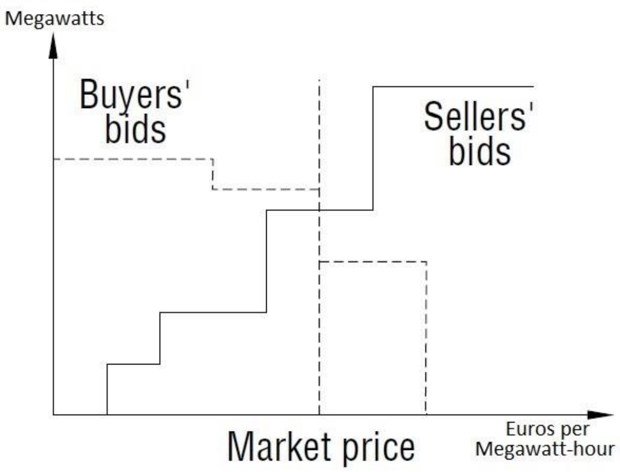

Figure 8: Symmetrical Pool, adapted from [38]

MASCEM simulates the Elspot – Nord Pool's day-ahead market in the following way: After the closing of the bidding, the market operator performs the matching process of the participants' offers. Since Elspot is a symmetric market, where there are buying and selling offers, the Elspot market uses linear interpolation as a means to obtain aggregated curves of selling and buying offers. Figure 8 illustrates the matching mechanism of the symmetric market.

The intersection point determines the market price and the volume of electricity for each period. After the market auction is finished, if congestion occurs in a connection point between areas, a market split takes place. Please refer to the congestion management model presented in [14] for details on how congestion is modelled through a service developed by TradeRES. The market split divides the market into two independent ones along congested market connection points. Once the division is performed, the market mechanism is run again for each area separately, and in case of congestion occurring once more in other points of the electrical grid, the market split process divides the network into more areas, following the same principle as before, repeating the entire process until there are no more congestion problems.

The sale offers with prices below the market price and the purchase offers with prices above the market price will be accepted in the market, and the price at which energy is traded is equal for all accepted offers (uniform market price for each period). For offers of flexible type, trading occurs in the same way, and these deals will apply in the periods when its use will maximize the market social welfare. When there are several offers of this kind, they will be ordered by price, with the lowest prices to be more likely to be accepted (always depending on the market price for each period).

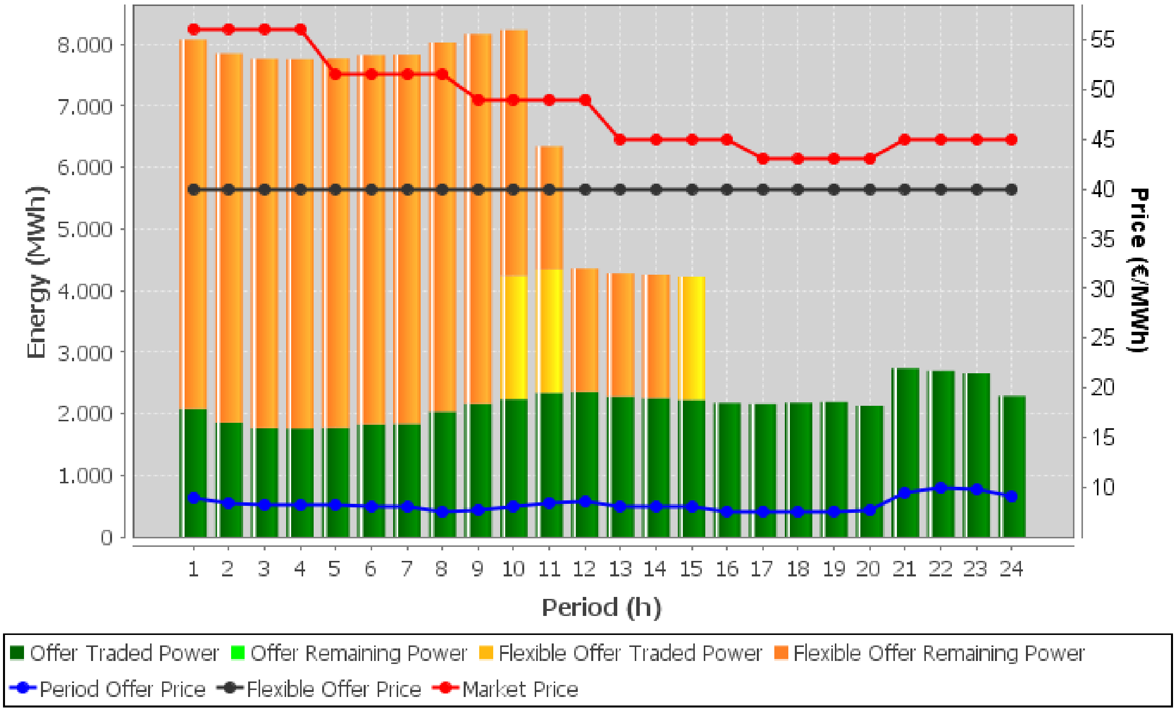

Figure 9: Market results for a test player using flexible orders, adapted from [38]

As an example, Figure 9 presents the results of an illustrative seller agent that, in addition to the single hourly orders, also submits three flexible hourly orders. These flexible hourly orders (available only to seller agents) allow the players to specify a fixed price and volume. The hour is not specified. The order will be accepted in the hour that optimizes the overall socioeconomic welfare of the market. A maximum of five flexible hourly orders is available per agent during a market session. In this scenario, three orders were submitted with the volume of 2000 MWh each, all three at the price of 40 €/MWh.

It is possible to observe from the chart of Figure 9 that during the first nine market periods (hours) none of the orders was accepted in spite of the bid price being below the established market price, since accepting the flexible orders in any of these periods would not maximize the market's social welfare. The orange bars indicate a total of 6000 MWh of unsold energy during these periods (referring to the total of the three flexible offers, of 2000 MWh each). The three submitted flexible hourly orders were accepted in the 10th, 11th and 15th periods. In these three periods, the total amount of energy of the order was sold. As can be seen by the graph of Figure 9, since the first flexible offer is accepted in period 10, only 4000 MWh remain to be negotiated in the 11th period. From these, 2000 MWh are accepted, and the remaining 2000 MWh, referring to the third and final flexible offer are negotiated in the following periods, being finally accepted in the 15th period. As mentioned before, the condition for the acceptance of each (or all) flexible offer is not only the proposed bid price, but also the maximization of the overall socioeconomic welfare of the market session, from the market operator's perspective. The calculation of the social welfare comprises several factors, such as the difference between the submitted sale / purchase bid prices and the actual market price, as well as the difference between the total demand and supply placed in the market. During these specific periods there is a peak of demand when compared to the available demand, hence these flexible sale orders are allocated in a way that the balance between demand and supply can be increased, while contributing to a slight decrease in the market price. The blue line in the chart of Figure 9 refers to the bid price referring to the inflexible power. As one can see, the blue line (sale bid prices) is always below the market price (red line), hence all inflexible power is sold during all periods of the considered day (dark green bars).

3.2.3. RESTrade

In contrast to actual market regulations, RESTrade already allows trading of shorter time units at balancing markets (BMs), 15 minutes instead of the traditional 60 minutes as indicated by the EU regulation on the internal market of electricity [39]. The stochastic behaviour of vRES makes BMs more unpredictable, especially for long time horizons. So, markets with a shorter time unit may be beneficial to vRES producers, by enabling them to reduce the level of uncertainty, since a higher level of time-granularity enables to reflect better the VRE variability, especially during extreme events [40]. In this sense, market products with shorter time units can reduce potential imbalances caused by vRES and, at the same time, improve the marketing capabilities for vRES at BM, thereby further reducing overall system imbalances.

When market players are not complying with their programmed schedule, deviations occur. Typically, vRES and consumers are the main sources of deviations. vRES have the technical capability to surpass some of their deviations, but economically might be more favourable to pay imbalance prices due to deviations than to curtail power [41, 42]. Keep in mind, that if curtailed, in contrast to conventional power plants, vRES do not save fuel costs but loose feed-in based remuneration payments. However, the penalties to players that do not comply with the BMs schedule can be significantly higher than the imbalance prices charged for other market deviations [8]. So, vRES can make bids in BMs, but they will have to respond to operational set-points requested by the TSO, even if not optimal concerning their primary resource. Then, vRES may need to reduce output below the potential production, curtailing power. Against this background, vRES should verify if it is economically more advantageous to participate in BMs, potentially curtailing power, or to pay penalties because of deviations. If they use their expected deviations from programmed schedules to participate in BMs vRES can get a higher remuneration if this leads to small amounts of curtailments, otherwise it may be preferable to pay penalties, depending on the BMs and imbalances prices [8]. In reality, deviations from programmed schedules may also be compensated for via intra-day trades as an alternative to paying imbalance prices. However, intra-day markets also close before real-time operation, so, vRES will always deviate from programmed schedules, which technically can be surpassed by vRES participation on BMs and complying with operational set points.

vRES should only make bids to BMs if they have extra power compared to their programmed schedule considering all trades: At the mFRR market, extra power in upwards or downwards direction can be offered, whereas at the aFRR market only upward extra power should be offered. To avoid economically infeasible curtailment, vRES may bid either the lowest 15-minute extra power, for the case of upward deviations, or a higher deviation for the mFRR market only, see Figure 10.

Considering an hourly aFRR or mFRR market, during the situation described in Figure 10(a), it is not possible for the vRES producer to participate in the aFRR capacity market or even on the upward mFRR energy market, because it cannot comply with a stable (operational set-point) upward dispatch that may be required by the TSO. In this case, it should only participate in the downward mFRR market considering a bid of 7.1 MW, but it will have to do several curtailments from hour 02:15 to hour 03:00. If the vRES producer bids a value above 7.1 MW, it will need to curtail more power and if it participates in the upward aFRR markets it cannot comply with the programming schedule, compromising the security of the power system and paying high penalties because of that. So, operationally and economically, it should only bid a maximum of 7.1 MW at the downward mFRR market.

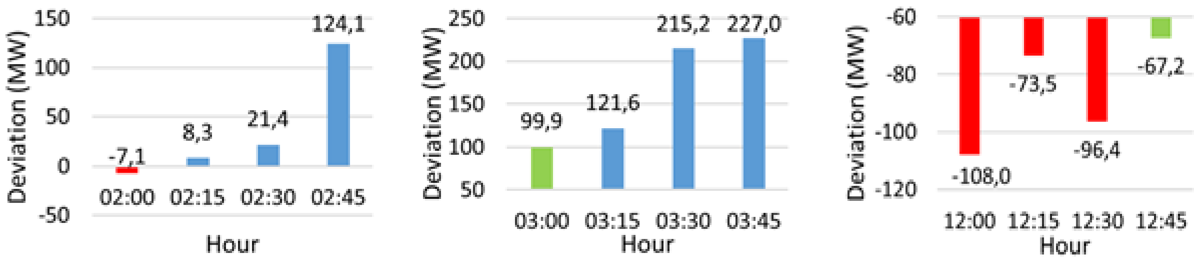

Figure 10: 15-min deviations from the programming schedule for a vRES producer: (a) not in the same direction, (b) stable up (blue bars) power (the lower green power defines the bid to aFRR and mFRR markets) and (c) stable down (red bars) power (the higher deviation defines the bid to mFRR market) [8]

Analysing Figure 10(b), it is possible to verify that the vRES producer should make bids to the upward mFRR market considering a maximum of 99.9 MW. If it bids a higher amount it cannot comply with the programming schedule, compromising the security of the system and paying high penalties. Considering the situation in Figure 10(c), the vRES producer should only make a bid for the downward mFRR market of 67.2 MW to avoid several curtailments. If it were to bid 108 MW, it could be requested to provide that amount of downward power during the period from 12:45 to 13:00 and would have to curtail more than 40 MW of power, which is economically not efficient. vRES can also participate in the aFRR market if there is a separate procurement for upward and downward capacity. Otherwise, it only can participate in the case of Figure 10(b) by bidding a capacity between -99.9 MW and 99.9 MW, which can lead to several curtailments in the case of being requested for providing downward energy.

Considering a 15-minute mFRR market, vRES producers do not need to address such issues, since their production variability decreases with a reduction of the market time unit, increasing their potential to support BMs. The 15-min deviations define the bids to the 15-min mFRR market and for the aFRR market in case of a separate procurement between upwards and downward capacity. The use of a time unit of 15 minutes can contribute to a high reduction in the vRES curtailments, deviations and overall balancing costs. A case study of the Portuguese balancing markets concludes that changing the time unit of the mFRR market to 15 minutes and allowing the participation of vRES, can contribute to a reduction of the energy deviations by 14.4%, reducing the balancing costs by 16% [8].

3.3 Model enhancements within TradeRES

The upcoming sections describe in detail new implementations of temporal flexibility options within TradeRES ABMs. Therefore, context and approach are given for each implementation, capabilities and restrictions are described and, if necessary, data requirements are specified.

3.3.1. AMIRIS

AMIRIS features two new implementations for temporal flexibility options, i.e., load shifting and variable market closure times. These are described in the following subsections.

3.3.1.1. Load shifting

AMIRIS uses a modelling approach for load shifting that builds upon the existing storage representation (see Section 3.2.1.2). Similar to that, the actual representation of the physical asset is separated from the strategy-building to market its capacities. In the following, the representation of a portfolio eligible for load shifting and its basic planning algorithm are described. Building on that, variations of that algorithm are explained. The variations refer to different marketing strategies for the associated load shifting portfolio.

- **Planning Algorithm**

The intertemporal decisions of load shifting are modelled using discretized load shift states and a *dynamic programming* approach to foster fast numeric solutions. Load shift states $Z = \{t_s, e\}$ are hereby defined to be a tuple of a shift time t_s and a discrete energy level e. The shift time represents the time duration that the load has been unbalanced. The minimum and maximum energy levels $e_{\min}$ and $e_{\max}$ define the bounds of the load shifting state grid. The state grid spans symmetrically around the balanced energy level e_0, i.e., the one that represents neither advancement nor delay of consumption. Energy levels below e_0 represent consumption delayed in time, whereas energy levels above e_0 indicate consumption advanced in time.

Regarding the shift time t_s, the following rules are employed:

- If the energy level reaches e_0 the shift time is set to 0.
- The shift time is increased by one for each time step in which the load shifting portfolio is unbalanced.
- If there is a change of the sign for the energy balance (by changing from load advancement to delay or vice versa) the shift time is reset to 1.

A maximum shift time exists after which the portfolio needs to be in a balanced state again. Besides accounting for the energy and shift time limits that define the set of allowed states Z, it has to be ensured that transitions from one load shift state to another do not violate power limits. The allowed difference in energy levels corresponds to the allowed maximum power. In upwards direction the power is constrained by the maximum additional load that can be taken by the agent, whereas in downwards direction the maximum load reduction is specified. Maximal shift in both upwards and downwards direction can be specified independently and are given as separate time series (typically in hourly resolution). If a portfolio cannot be used for load shifting at all in a certain timeframe, both upshift and downshift limits are set to zero.

Figure 11 shows an example for selecting feasible next states based on the assumption of a starting state of $(t_s = 1, e = 3)$ and a power limit of ± 2. Several options exist:

- Balance out the previous load shift and return to e_0. This also resets the shift time to zero resulting in the blue transition to state $(0, 2)$.
- Continue the load shift in the current direction (orange arrows). This includes either remaining at the same energy level or further shifting in the same (upward) direction. In both cases the shift time is increased and the two allowed follow-up states are either $(2, 3)$ or $(2, 4)$.
- Reverse the load shift (green arrow) with maximum downward power. Due to the reversed sign of the energy level $e < e_0$ the shift time is set to 1.

Other discretised load shift states cannot be reached in this example due to the energy and power restrictions and the rules on shift times. Note that the load shift states $(t_s > 0, e = 2)$ are not available, since the shift time is defined to be 0 at the balanced energy level e_0.

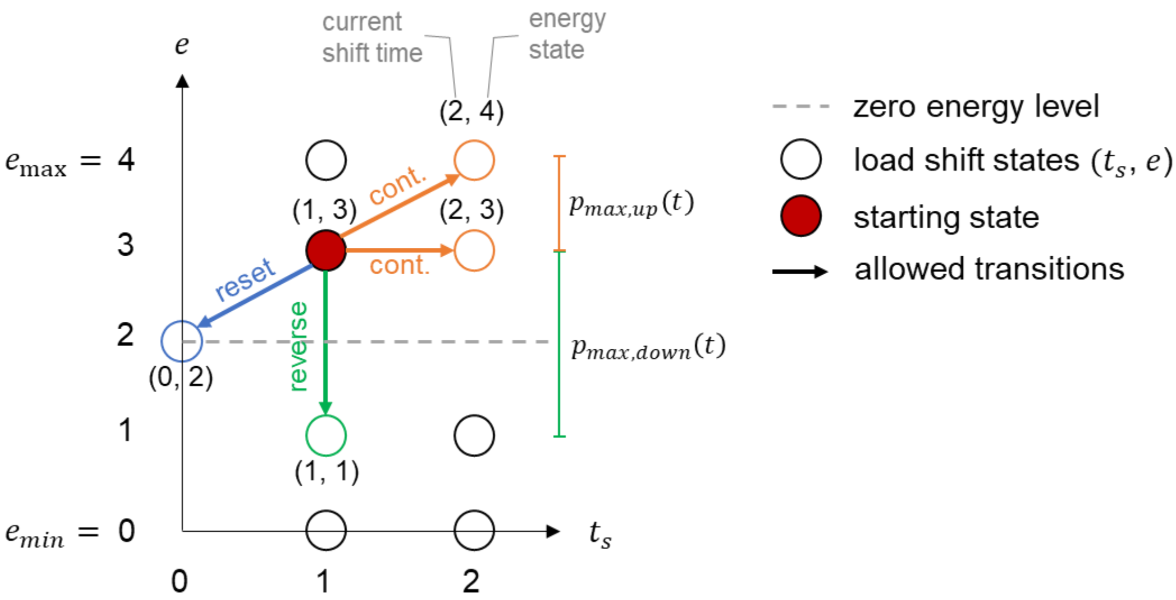

Figure 11: Load-shift transitions from starting state (red dot) to available follow-up states indicated by arrows on the discretised state grid (shift-times on the x-axis and energy levels on the y-axis); unreachable states, e.g., $(0,3)$ or $(1,2)$ not depicted

In addition to the discussed transitions, the shift time can also be prolonged beyond the maximum shift time limit. This can be justified by interpreting the controlled load shifting portfolio not as a single device, but a composition of multiple devices. Then, the portfolio can be split virtually. Any load shift energy is assumed not to be distributed equally across all devices but assigned to only some devices within the portfolio. The other devices within the portfolio can then be used to counteract the actions of the devices that need to balance out their previous shift once reaching maximum shift time. Thus, one part of a portfolio is shifted in one direction while the other part is shifted in the other direction. This results in effectively prolonging the current shift cycle. While this results in a net-zero energy balance, additional costs for the portfolio-internal load shift need to be considered. This option to prolong the shift time is also included in AMIRIS. However, not more than the maximum power in upward or downward direction can be shifted with this operation – otherwise power limits would be violated as shown by [43, p. 842].

The employed algorithm needs to find the best path across the load shift states that does not violate the aforementioned restrictions regarding energy levels, shift times and available power. Therefore, dynamic programming is used in the following way: Starting at an initial state of the portfolio, the performance of all feasible follow-up states is evaluated regarding their strategic target (see following subsection on Strategies). Cost and benefits for each transition are added to the potential cost and benefits of the follow-up state associated with the next time step. Comparison of all feasible transitions and their performance leads to the identification of the best choice for each assessed initial state.

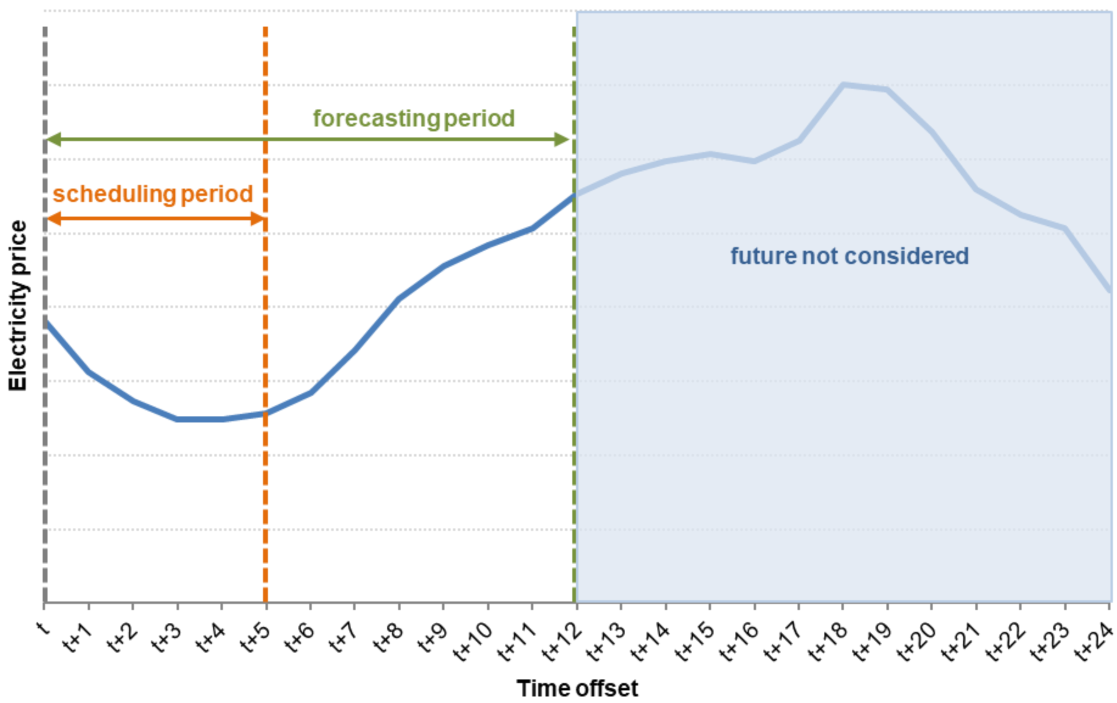

Figure 12: Schematic representation of the time intervals for forecast and scheduling

The result quality of the described algorithm is subject to several parameters that can be controlled in the AMIRIS model configuration: the granularity of the energy levels, the forecast period and the scheduling period. All of them can have a considerable influence on the precision of the results. The granularity of the energy levels determines how many different load-shifting options are assessed for finding the best transition. For instance, doubling the number of assessed energy levels also doubles the precision of the result while the computation time increases by four. The forecast period (see Figure 12) determines the number of considered future time steps (starting at the current time *t)* when optimising the dispatch schedule. Any information beyond the forecast horizon is not considered during optimisation – a restriction that is also valid for real-world planning processes.

The scheduling period determines the number of future time steps of a dispatch plan. A new schedule must be created after the scheduling period has expired. The scheduling period can be shorter than the forecasting period (down to an extreme of a single time step). In this case the schedule is renewed after the scheduling period has passed and allows agents to consider future information not considered when the first schedule was created (rolling horizon).

- **Strategies**

There are two different strategies available to market load shifting capacities. One seeks to minimize system costs while the other aims at maximizing the obtained profits. The latter strategy does allow for a consideration of taxes and levies while the first one only accounts for system costs.

The *system-cost-minimization strategy* requires a perfect forecast of the marginal costs of all power plants in the system and their intended bids. This enables the strategy to consider any changes of the merit order and associated changes in the system cost caused by additional or reduced demand. Variable costs for load shifting are considered to add to the system cost as well. Then, the dispatch schedule for an associated load shifting portfolio is created in such a way that the total system costs are minimized.

The *profit-maximizing strategy* also requires a perfect forecast. However, for this strategy the power prices including possible price changes resulting from changing the load suffice. Marginal cost associated with each bid are disregarded (power prices may deviate from the marginal costs in case power plants apply markdowns or markups on top of their marginal costs). The profit-maximizing strategy calculates the expected revenues from offering capacity to the market. The offered price is set to be just above or below the projected clearing price (including changes caused by the load shift) in dependence of the shift direction (upwards or downwards). The strategy subtracts variable costs, taxes and levies from the expected profits and then selects the most profitable path for dispatch and associated bids for each time step along the forecasting interval.

3.3.1.2. Variable market closure lead times

The day-ahead electricity markets of most European bidding zones hosted by EPEX close at 12:00 CET the day before. This means that the gate closure of the day-ahead market has a lead time of 12 to 36 hours until realisation of possible deliveries. Forecasts for relevant electricity market variables like renewable power generation or demand have even greater lead times, since they are required for the bid creation and are thus typically required several hours before gate closure, further reducing their accuracy. Figure 13 depicts an example of forecast uncertainty derived from ENTSO-E data for renewable feed-in and demand in Germany, July 2018. Although the four depicted variables are also subject to patterns related to the hour of the day, it becomes clear that their forecast uncertainty rises towards more distant times.

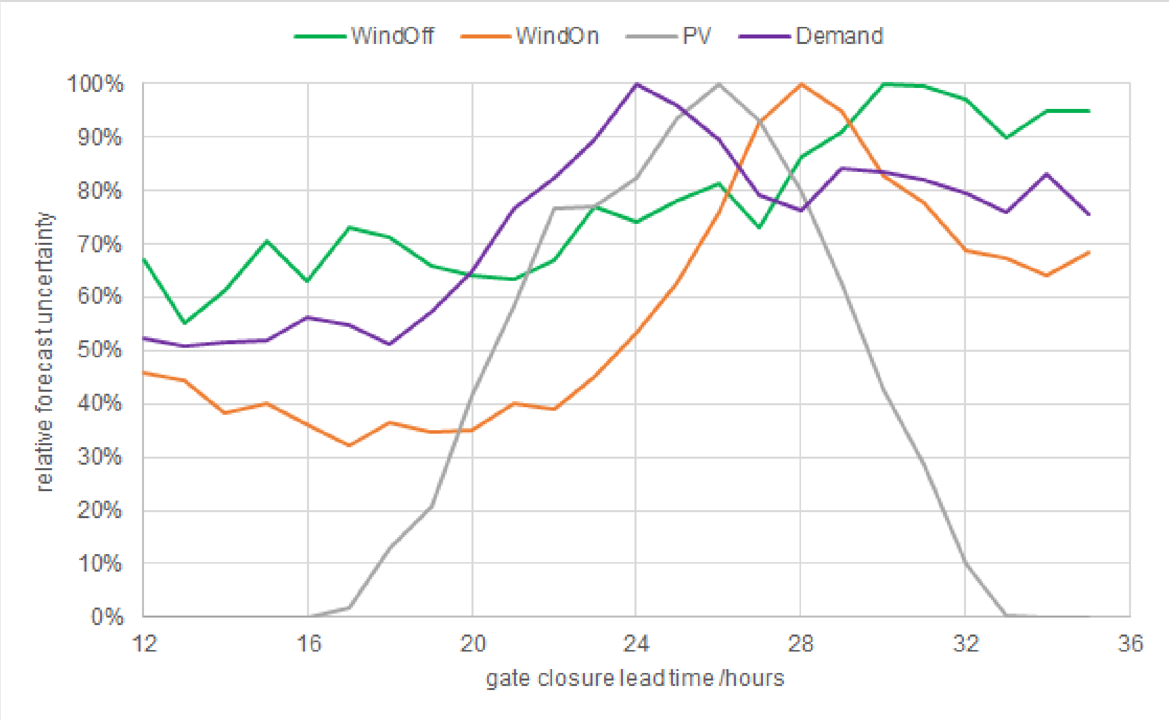

Figure 13: Relative forecast error for day-ahead forecasts of demand, wind offshore, wind onshore and PV generation in Germany, average of 4 weeks in July 2018; original data from ENTSO-E[5]

[5] https://transparency.entsoe.eu

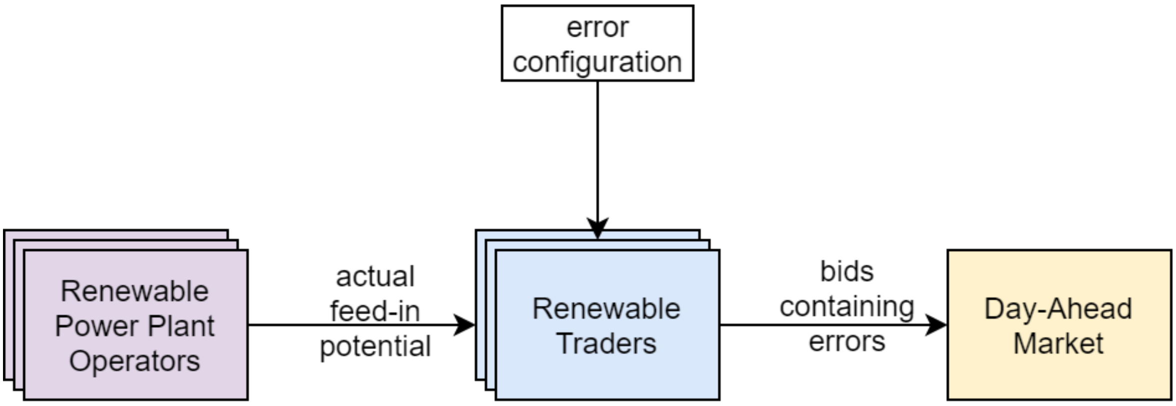

Figure 14: Schematic representation of feed-in error consideration in AMIRIS

AMIRIS considers this uncertainty of forecasts. A schematic representation is shown in Figure 14. The renewable plant operators deliver perfect information about their future feed-in potential to their associated traders. The trading agents may then add random errors to the otherwise perfect forecast when creating their bids[6] in order to simulate real-world forecast uncertainty. These bids (including errors) are then forwarded to the energy exchange and influence the day-ahead electricity price. Once the bids are awarded by the energy exchange, the traders need to compensate for their previous errors. Since AMIRIS does not feature an additional intraday market, bidding errors need to be compensated via balance energy. The associated costs for balance energy then impact the trader's profit.

To simulate the effects of different market closure lead times with a rolling horizon model such as AMIRIS (see Section 3.2.1.3), the trader agent's configuration will allow to specify the relative error level for electricity amounts in bids. The relative error is represented by a minimum and maximum value for each time segment (e.g. hour) of the day and is then randomly chosen by drawing from, e.g., Gaussian or Uniform distributions within the bounds corresponding to that time segment.

This approach allows to consider error levels at a specific time of the day to reflect the time delta between market closure and specified time of delivery. Longer or shorter gate closure lead times can then be emulated by employing higher or lower error levels for the bids. This approach also correctly considers the impact of the gate closure lead times on electricity prices and trader profits. It is also compatible with emulating different implementations of rolling market clearing.

[6] Trading agents try to sell their fully available quantities at the market.

Two examples illustrate the mechanics: To simulate the current market rules with 12 to 36 hours lead times, one could associate uncertainties corresponding to a 12+x hour forecast with the first hour of the day, constantly increasing towards the final hour of the day with uncertainties corresponding to a 35+x hours forecast lead time. Here, x represents the forecast lead time with respect to the moment of gate closure. To simulate a market with 6-hour gate closure lead times and a rolling market clearing for 4 hours each, the uncertainty at the first hour of the day could correspond to a 6+x hour forecast, slightly increase to 9+x hour forecast in the fourth hour of the day and then drop again to 6+x hour forecast error levels. This pattern is then repeated five more times throughout the day (see also Figure 5).

3.3.2. MASCEM

MASCEM [7, 26] was enhanced to incorporate load shifting, load shedding and real-time pricing mechanics. The following subsections contain detailed explanations of how these features were implemented.

3.3.2.1. Load Shifting and Shedding

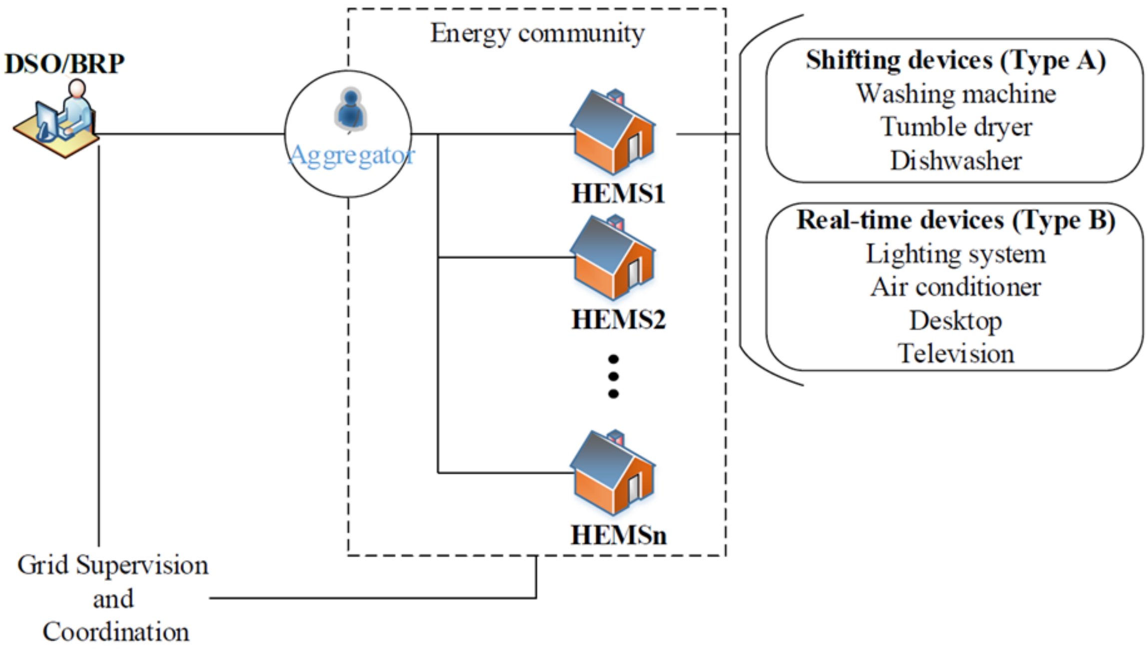

Figure 15: Overview of MASCEM's load shifting flexibility model

The incorporation of load shifting and shedding capabilities in MASCEM market models has been designed and is being implemented taking advantage of aggregators as intermediaries between the market and the consumer and prosumer. In this model (see also Figure 15), the aggregator has contracts with end-users (consumers/prosumers), which may have a home energy management system (HEMS) with different devices with demand response capabilities. For demand response, it considers two types of devices, one that allows consumption to be shifted to a different period (e.g., washing machines, tumble dryers, or dishwashers), and another with real-time control capabilities where no shifting is possible (e.g., lighting system or air conditioners), but only reduction or curtailment at the same time. The aggregator is prepared to respond to a flexibility request from a Distribution System Operator (DSO) to address local grid congestion or a Balance Responsible Party (BRP) in need of energy to balance its portfolio, who pays monetary compensation for each power unit of flexibility provisioned. The monetary compensation is calculated according to the model described below, aiming at minimizing the costs of the DSO/BRP. It also makes use of a flexibility management system to re-schedule appliances and match, as close as possible, the flexibility curve procured by the DSO. This flexibility curve results from the power network validation performed by the DSO after the market results are achieved. Once the market results at a certain time horizon (e.g. day-head) are determined according to the forecasts available at that time, the DSO will validate the power network, and, if problems (e.g. congestion) are identified, a request for flexibility is launched for these specific time periods. In this way, it is possible to re-schedule the necessary amount of consumption in order to avoid the foreseen network problems, at the cost of paying a monetary compensation to the target consumers.

In addition, end-users have the capability of registering devices for flexibility provision and configuring their preferences regarding allowed shiftable times, expected remuneration due to flexibility activation, a priority of the available devices for activation, amongst others.

Besides, two assumptions are necessary when addressing the model. The first one is that all the required infrastructure is available for achieving the management and control of load, and the second is that the DSO/BPR and the aggregator have access to forecasts of baseline power consumption provided by a third party.

- **Algorithm**

The problem can be modelled with mixed-integer non-linear programming in which the aggregator strives to match a flexibility request from the DSO/BRP, paying a remuneration to the households participating in the demand response program according to their preferences and the modification of their baseline profile.

In this model, let $A = \{1, \dots, N_I\}$ be the set of all appliances with shifting capabilities, and $B = \{1, \dots, N_J\}$ the set of all appliances with real-time control capabilities registered in the aggregator's EMS. Each appliance with shifting capabilities is characterized by tuple $A_i = [t_{\text{start}(i)}, O_{(i)}, p_{A(i,k)}] \in A$, where $t_{\text{start}(i)}$ represents the baseline starting period of functioning program of appliance i, $O_{(i)}$ is the time duration of a given program of appliance i, and $p_{A(i,k)}$ is the power profile of a given functioning program of appliance i defined in the interval $k = [1, \dots, O_{(i)}]$.

On the other hand, each appliance with real-time control is characterized by a tuple $B_j = [p_{\text{B}(j)}, I_{\text{start}(j,t)}] \in B$, where $p_{B(j)}$ is the maximum power of appliance j, and $\mathrm{I}_{\mathrm{start}(j,t)}$ is a number in the range [0,1] representing a percentage of the baseline consumption intensity of appliance j in time t.

It is assumed that users have access to a HEMS interface in which they can configure their preferences. A tuple $\mathrm{Pref}_{A(i)} = [t_{\mathrm{allow}(i)}, D_{\mathrm{allow}(i)}, C_{A(i)}]$ is defined by the user, specifying the start of the allowed time window $t_{\mathrm{allow}(i)}$, the window duration $D_{\mathrm{allow}(i)}$ for aggregator's control access, and the expected remuneration $C_{A(i)}$ (in EUR) to be received if device i is shifted from the baseline starting period $t_{\mathrm{start}(i)}$ to a different period in the allowed window. With these parameters, the shifting periods of devices type A are constrained by the user as follows:

$$t_{\mathrm{allow}(i)} \leq t_{\mathrm{new}(i)} \leq t_{\mathrm{allow}(i)} + D_{\mathrm{allow}(i)} \tag{1}$$

where $t_{\mathrm{new}(i)}$ is the new starting period of appliance i.

Similarly, a tuple $\mathrm{Pref}_{B(j)} = [t_{\mathrm{allow}(j)}, D_{\mathrm{allow}(j)}, I_{\mathrm{min}(j)}, I_{\mathrm{max}(j)}, C_{B(j)}]$, defines the allowed periods where intensities of appliances of type B can be modified (i.e., $t_{\mathrm{allow}(j)}, D_{\mathrm{allow}(j)}$), the maximum allowed reduction/increase of consumption of such devices (i.e., $I_{\mathrm{min}(j)}, I_{\mathrm{max}\,(j)}$), and the expected remuneration $C_{B(j)}$ (in EUR per kWh) to be received for the amount of power reduction/increase of device j in the allowed window. Thus, the modification of power profiles of devices type B is constrained by the user as follows:

$$I_{\mathrm{min}(j)} \leq \mathrm{I}_{\mathrm{new}(j)} \leq I_{\mathrm{max}(j)} \tag{2}$$

$$I_{\mathrm{new}(j,t)} = \begin{cases} I_{\mathrm{mod}(j,t)} & \text{if} \quad t_{\mathrm{allow}(j)} \leq t \leq t_{\mathrm{allow}(j)} + D_{\mathrm{allow}(j)} \\ I_{\mathrm{start}(j,t)} & \text{otherwise} \end{cases} \tag{3}$$

where $\mathrm{I}_{\mathrm{new}(j,t)}$ and $I_{\mathrm{mod}(j,t)}$ are variables in the range [0,1] for each $t \in N_T$ defining a modification (in percentage) of the baseline profile and $I_{\mathrm{start}(j,t)}$ being a number in the range [0,1] (representing a percentage of the consumption).

The flexibility provisioned by the aggregator (i.e., $F_{\mathrm{agg}(t)}$) is defined as the difference between the baseline profile, and the new scheduled profile as follows:

$$F_{\mathrm{agg}(t)} = P_{\mathrm{base}(t)} - P_{\mathrm{flex}(t)} \tag{4}$$

where $P_{\mathrm{base}(t)}$ is the baseline profile and $P_{\mathrm{flex}(t)}$ is the resulting profile after re-scheduling appliances? Notice that a third party should determine the baseline profile since it represents the expected power consumption of the appliances if no re-schedule or modification is performed. It is assumed that the aggregator has the information regarding the baseline consumption of each household, and it uses this information to determine the flexibility offer.

Equations (5), (6), (7) are used to represent the baseline profile:

$$P_{\mathrm{base}(t)} = \sum_{i=1}^{N_I} A_{\mathrm{base}(i,t)} + \sum_{j=1}^{N_J} B_{\mathrm{base}(j,t)} \tag{5}$$

$$\mathrm{A}_{\text{base}(i,t)} == \begin{cases} p_{\mathrm{A}(i,t-t_{\text{start}(i)}+1)} \quad \text{if} \\ t_{\text{start}(i)} \leq t \leq t_{\text{start}(i)} + O_{(i)} - 1 \\ 0 \qquad \text{otherwise} \end{cases} \tag{6}$$

$$B_{\text{base}(j,t)} = p_{B(j)} * I_{\text{start}(j,t)} \tag{7}$$

where Eq. (5) captures the aggregated power of all appliances at a given time t. Eq. (6) captures the power of shifting appliance i at a given time t, $t_{start(i)}$ is the baseline starting period of operation, and $O_{(i)}$ is the number of periods of the operation program of device i (e.g., considering 15 min periods and a $t = 1$ corresponding to 00:00 am, $t = 2$ to 00:15 am, $t = 3$ to 00:30 am, etc.; a washing machine can start its baseline operation at $t_{\text{start}(i)} = 5$ – corresponding to 01:00 am, and have a duration of operation program of $O_{(i)} = 9$ – which means that the machine operates for 135 min and will finish its operation at period $t_{\text{start}(i)} + O_{(i)} = 14$ –corresponding to 03:15 am). Eq. (7) captures the baseline power of appliance j at time t considering intensity $\mathrm{I}_{\text{start}(j,t)}$ being a number in the range [0,1]. Notice that variables $t_{\text{start}(i)}$ and $\mathrm{I}_{\text{start}(j,t)}$ are input parameters to represent baseline consumption patterns.

On the other hand, the aggregator determines new starting periods $t_{\text{new}(i)}$ for the appliances with shifting capabilities and new intensities $\mathrm{I}_{\text{new}(j,t)}$ for the appliances with reduction capabilities. Eqs. (8)-(10) represent the determination of the new consumption profile:

$$P_{\text{flex}(t)} = \sum_{i=1}^{N_I} A_{\text{flex}(i,t)} + \sum_{j=1}^{N_J} B_{\text{flex}(j,t)} \tag{8}$$

$$\mathrm{A}_{\text{flex}(i,t)} = \begin{cases} p_{A(i,t-t_{\text{new}(i)}+1)} \quad \text{if} \\ t_{\text{new}(i)} \leq t \leq t_{\text{new}(i)} + O_{t(i)} - 1 \\ 0 \qquad \text{otherwise} \end{cases} \tag{9}$$

$$B_{\text{flex}(j,t)} = p_{B(j)} * \mathrm{I}_{new(j,t)} \tag{10}$$

where Eq. (8) represents the new consumption profile after determining optimal starting periods $t_{\text{new}(i)}$ (see Eq. (9)) and intensities $\mathrm{I}_{\text{new}(j,t)}$ (see Eq. (10)) for all the appliances managed by the aggregator.

In order to maximize the aggregator's profits, the objective function can be modelled as the minimization of the remuneration to be paid to the households plus a penalty for the mismatch of flexibility procured by the DSO/BRP. The goal is therefore, to decide on the optimal monetary compensation to provide to consumers, while adjusting the flexibility/shifting of each device according to the needs of the DSO/BRP and the possibilities specified for each device, as follows:

Minimise $f = \left(\sum_{i=1}^{N_I} \mathrm{Rem}_{A(i)} + \sum_{j=1}^{N_J} \mathrm{Rem}_{B(j)}\right) + C_{\text{DSO}} \cdot F_{\text{match}}$ (11)

$$\mathrm{Rem}_{A(i)} = \begin{cases} C_{A(i)} & \text{if } t_{\mathrm{start}(i)} \neq t_{\mathrm{new}(i)} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{Rem}_{B(j)} = C_{B(j)} \cdot \sum_{t=1}^{N_T} \left| B_{\mathrm{base}(j,t)} - B_{\mathrm{flex}(j,t)} \right|$$

$$F_{\mathrm{match}} = \sum_{t=1}^{N_T} \left| F_{\mathrm{agg}(t)} - F_{\mathrm{DSO}(t)} \right|$$

where the first term of Eq. (11) corresponds to the monetary compensation paid for shifting device i (a flat payment $C_{A(i)}$ in EUR is considered despite how many periods the device is shifted); the second term corresponds to the remuneration given for the modification of the baseline profile of devices type B (where $C_{B(j)}$ is a compensation paid in EUR/kWh modification); and the third term corresponds to a penalty, C_{DSO} in EUR/kWh, paid for the mismatch between the flexibility procured by the DSO ($F_{\mathrm{DSO}(t)}$) and the flexibility provided by the aggregator ($F_{\mathrm{agg}(t)}$) in each period t.

3.3.2.2. Real Time Pricing and Battery Storage Systems

MASCEM features new implementations for scheduling of battery energy storage (BES) in joint energy and ancillary services markets. It consists of an energy-constrained self-scheduling model for owners/participation of BES, focusing on the provision of temporal flexibility considering real-time pricing.

The proposed model is formulated based on the profit maximization of BES within the expected life cycle. In the short-term scheduling, the lifetime and capacity degradation of batteries are modelled by the energy throughput concept, which is basically the total amount of energy a battery can be expected to store and deliver over its lifetime [44]. Therefore, the optimal scheduling is determined based on the storing and delivering energy guaranteed by the manufacturer, the planned lifetime, and the energy constraint of batteries.

For this purpose, two assumptions must be considered. Firstly, it is assumed that BES can buy/sell its energy from the energy market in charging/discharging modes, and bid in energy and ancillary services markets, simultaneously. Secondly, BES are assumed to be able to participate in down and up-regulation services in charging and discharging modes, respectively. In other words, when in charging/discharging mode, the battery can be used as a load/generation unit, respectively. Considering that an up-regulation situation is usually happening in a high price period, and the market operator shall increase the generation or decrease consumption, in order to prevent the dissatisfaction of consumers, the market operators prefer not to use load reduction or load shedding. Moreover, the renewable resources' owner also prefers to sell its energy within high price periods. Therefore, the battery is supposed to participate in up-regulation service in the discharging mode.

In opposition to that, down-regulation situations are usually happening in low price periods. Subsequently, the market operator shall decrease generation or increase consumption. In contrast to the previous case, the renewable resources' owner prefers to purchase more energy in low price periods. Thus, the system operator prefers to increase consumption during the low-price period to optimize the load profile.

- **Algorithm**

Before presenting the algorithm, the following nomenclature must be taken into consideration.

Indices and Sets

t, T	Index and set of time
j, J	Index and set of intra-hourly
l, NL	Index and set of BES lifetime

Constants and Parameters

E^{Rated}	Rated capacity of BES (MWh)
$E^{\min}$	Minimum capacity of BES (MWh)
π^{SE}	Price of selling to the energy market (\$/MWh)
π^{BE}	Price of buying from the energy market (\$/MWh)
π^{DR}	Down regulation price in regulation market (\$/MWh)
π^{UR}	Up regulation price in regulation market (\$/MWh)
π^{CH}	Energy charging price in regulation market (\$/MWh)
π^{RT}	Real-time energy price in regulation market (\$/MWh)
RR^{Ch}	Charging ramp-rate (MW)
RR^{Dch}	Discharging ramp-rate (MW)
M^*	Large enough constant
H^{LT}	Lifetime throughput energy (MWh)
H^{AT}	Annual throughput energy (MWh/year)
ψ	Annual degradation of BES capacity (%)
W	Working days per year (day)
δ	Variation interval of uncertain parameter
ε	Confidence level of uncertain parameter

r Interest rate (%)

Decision variables

$\Delta E^{E,ch}$ Charging bid in energy market (MWh)

$\Delta E^{E,dch}$ Discharging bid in energy market (MWh)

ΔE^{E} Energy bid in energy market (MWh)

ΔE^{RS} Energy bid in regulation service (MWh)

ΔE^{UR} Energy bid in up-regulation market (MWh)

ΔE^{DR} Energy bid in down-regulation market (MWh)

E Stored energy of BES (MWh)

μ, λ Lagrange multiplier

A^{*} Auxiliary variable for linearization

Binary Variables

U Charging/discharging status ($U = 1$ for discharging, $U = 0$ for down charging)

υ Regulation service status ($\upsilon = 1$ for up regulation, $\upsilon = 0$ for down regulation)

Based on the nomenclature presented, for the energy market, the total traded energy of BES in the operational period t can be formulated by the system of equations (1) consisting of equations (1a) to (1f). It shall be noted that the binary variable U represents charging ($U = 0$) or discharging mode ($U = 1$) of the battery. The second term of (1a) is nonlinear. Therefore, via the auxiliary variable A^{E} and big M theory [45], ΔE^{E} is linearized by constraints (1b)-(1e).

$$\begin{aligned} \Delta E_t^{E} &= \Delta E_t^{E,ch}.(1-U_t) - \Delta E_t^{E,dch}.U_t \\ &= \Delta E_t^{E,ch} - U_t.(\Delta E_t^{E,dch} + \Delta E_t^{E,ch}) \end{aligned} \quad :\forall t \tag{1a}$$

$$\Delta E_t^{E} = \Delta E_t^{E,ch} - A_t^{E} \quad :\forall t \tag{1b}$$

$$A_t^{E} \le M^{E}.U_t \quad :\lambda_t^{1}, \forall t \tag{1c}$$

$$A_t^{E} \le \Delta E_t^{E,dch} + \Delta E_t^{E,ch} \quad :\lambda_t^{2}, \forall t \tag{1d}$$

$$A_t^{E} \ge \Delta E_t^{E,dch} + \Delta E_t^{E,ch} - M^{E}.(1-U_t) \quad :\lambda_t^{3}, \forall t \tag{1e}$$

$$A_t^{E}, \Delta E_t^{E,ch}, \Delta E_t^{E,dch} \ge 0 : \ \forall t \tag{1f}$$

It should be noted that charging and discharging efficiencies are fixed terms and they do not have any impact on the optimization procedure. Therefore, without loss of generality, it is supposed that charging and discharging efficiencies are equal to one.

Same as (1), the energy market payoff is linearized by the auxiliary variable A^{PE} and big value M^{PE} as represented in the following system of equations (2):

$$Pay^E = \sum_{t=1}^{T} \pi_t^{SE}.\Delta E_t^{E,dch}.U_t - \pi_t^{BE}.\Delta E_t^{E,ch}.(1-U_t)$$
$$= \sum_{t=1}^{T} \left(\pi_t^{SE}.\Delta E_t^{E,dch} + \pi_t^{BE}.\Delta E_t^{E,ch} \right).U_t - \pi_t^{BE}.\Delta E_t^{E,ch} \tag{2a}$$

$$Pay^E = \sum_{t=1}^{T} A_t^{PE} - \pi_t^{BE}.\Delta E_t^{E,ch} \tag{2b}$$

$$A_t^{PE} \le M^{PE}.U_t : \lambda_t^4, \forall t \tag{2c}$$

$$A_t^{PE} \le \pi_t^{SE}.\Delta E_t^{E,dch} + \pi_t^{BE}.\Delta E_t^{E,ch} : \forall t \tag{2d}$$

$$A_t^{PE} \ge \pi_t^{SE}.\Delta E_t^{E,dch} + \pi_t^{BE}.\Delta E_t^{E,ch} - M^{PE}.(1-U_t) : \forall t \tag{2e}$$

$$A_t^{PE} \ge 0 : \forall t \tag{2f}$$

The participation level of BES in the reserves ancillary service depends on the regulation incentives and prices as BES determines the up and down regulation bids. Moreover, BES can participate in up/down regulation in charging/discharging mode, respectively. The bidding strategy of BES in the regulation market can be represented as follows:

$$\Delta E_{t,j}^{RS} = \Delta E_{t,j}^{DR}.(1-\upsilon_{t,j}) - \Delta E_{t,j}^{UR}.\upsilon_{t,j} : \forall t, \forall j \tag{3a}$$

$$\Delta E_{t,j}^{DR}, \Delta E_{t,j}^{UR} \ge 0 : \forall t, \forall j \tag{3b}$$

The status of BES in up regulation/down regulation service is specified by the binary variable υ (for $\upsilon = 1$ up-regulation, and $\upsilon = 0$ for down-regulation), and $\Delta E_{t,j}^{RS}$ is linearized as follows:

$$\begin{aligned}\Delta E_{t,j}^{RS} &= \Delta E_{t,j}^{DR} - \upsilon_{t,j}.(\Delta E_{t,j}^{DR} + \Delta E_{t,j}^{UR}) \\ &= \Delta E_{t,j}^{DR} - A_{t,j}^{RS}\end{aligned} \quad : \forall t, \forall j \tag{4a}$$

$$A_{t,j}^{RS} \le M^{RS}.\upsilon_{t,j} : \lambda_{t,j}^5, \forall t, \forall j \tag{4b}$$

$$A_{t,j}^{RS} \le (\Delta E_{t,j}^{DR} + \Delta E_{t,j}^{UR}) : \lambda_{t,j}^6, \forall t, \forall j \tag{4c}$$

$$A_{t,j}^{RS} \ge (\Delta E_{t,j}^{DR} + \Delta E_{t,j}^{UR}) - M^{RS}.(1-\upsilon_{t,j}) : \lambda_{t,j}^7, \forall t, \forall j \tag{4d}$$

$$A_{t,j}^{RS} \ge 0 : \forall t, \forall j \tag{4e}$$

In regulation service, BES receives the capacity and deployment payments, which are calculated based on the accepted capacity and deployed energy in the ancillary service market, respectively.

Another assumption is that all the capacity of regulation bid will be deployed by the local market operator in the real-time operation. Moreover, it is supposed that BES can participate in up and down-regulation services by discharging and charging of energy, respectively. Therefore, BES income in from the regulation market is:

$$Pay^{RS} = \sum_{t=1}^{T}\sum_{j=1}^{J}\left(\left(\pi_{t,j}^{DR} - \pi_{t,j}^{CH}\right).\Delta E_{t,j}^{DR}.(1-\upsilon_{t,j}) + \left(\pi_{t,j}^{UR} + \pi_{t,j}^{RT}\right).\Delta E_{t,j}^{UR}.\upsilon_{t,j}\right) \tag{5}$$

Since (5) is nonlinear, it is rewritten as follows:

$$Pay^{RS} = \sum_{t=1}^{T}\sum_{j=1}^{J}\left(\pi_{t,j}^{DR} - \pi_{t,j}^{CH}\right).\Delta E_{t,j}^{DR} - \left(\pi_{t,j}^{CH} - \pi_{t,j}^{DR}\right).\Delta E_{t,j}^{DR}.\upsilon_{t,j} + \left(\pi_{t,j}^{UR} + \pi_{t,j}^{RT}\right).\Delta E_{t,j}^{UR}.\upsilon_{t,j} \tag{6}$$

and the nonlinear parts are linearized via big M reformulations. Therefore:

$$Pay^{RS} = \sum_{t=1}^{T}\sum_{j=1}^{J}\left(\pi_{t,j}^{DR} - \pi_{t,j}^{CH}\right).\Delta E_{t,j}^{DR} - A_{t,j}^{DR} + A_{t,j}^{UR} \tag{7a}$$

$$A_{t,j}^{DR} \le M^{RG}.\upsilon_{t,j} :\ \lambda_{t,j}^{8}, \forall t,\ \forall j \tag{7b}$$

$$A_{t,j}^{UR} \le M^{RG}.\upsilon_{t,j} :\ \lambda_{t,j}^{9}, \forall t,\ \forall j \tag{7c}$$

$$A_{t,j}^{DR} \le \left(\pi_{t,j}^{CH} - \pi_{t,j}^{DR}\right).\Delta E_{t,j}^{DR} :\ \forall t,\ \forall j \tag{7d}$$

$$A_{t,j}^{UR} \le \left(\pi_{t,j}^{UR} + \pi_{t,j}^{RT}\right).\Delta E_{t,j}^{UR} :\ \forall t,\ \forall j \tag{7e}$$

$$A_{t,j}^{DR} \ge \left(\pi_{t,j}^{CH} - \pi_{t,j}^{DR}\right).\Delta E_{t,j}^{DR} - M^{RG}.(1-\upsilon_{t,j}) :\ \forall t,\ \forall j \tag{7f}$$

$$A_{t,j}^{UR} \ge \left(\pi_{t,j}^{UR} + \pi_{t,j}^{RT}\right).\Delta E_{t,j}^{UR} - M^{RG}.(1-\upsilon_{t,j}) :\ \forall t,\ \forall j \tag{7g}$$

$$A_{t,j}^{DR}, A_{t,j}^{UR} \ge 0 : \forall t,\ \forall j \tag{7h}$$

Considering that charging price can be defined as the price of consuming energy in real-time for charging of the battery that is deployed in down regulation, it shall be noted that the charging price can be specified based on the real-time price, which is greater than the regulation capacity price ($\pi^{CH} > \pi^{DR}$).

Continuous charging and discharging cycles of BES could decrease its lifetime and the expected profit, consequently. Therefore, the lifespan is a crucial parameter that shall be considered in the scheduling of BES. It shall be noted that Depth-of-Discharge (DOD) is the common method for modeling the lifetime of BES. DOD determines the remain lifetime based on the percentage of the energy that has been discharged from the fully rated capacity, which can be seen in

$$DOD_t\% = \frac{E^{Rated} - E_t}{E^{Rated}} \times 100 \tag{8}$$

The main drawback of DOD is that it does not reflect the BES capacity degradation over the lifetime. Moreover, manufacturers provide the allowable life cycle of batteries based on DOD that represents discharged depth from the fully charged state. Evidently, there is no guarantee in hourly scheduling of BES that the discharge cycles are started from the fully charged state. Therefore, the energy throughput concept is proposed by manufacturers to solve this problem. The energy throughput is the total amount of energy that can be charged and discharged within the lifetime of batteries, and it is not affected by the depth of charge or discharge. According to the battery energy throughput and planned lifetime, the energy constraint and optimal scheduling of BES within the planning period can be determined. According to the throughput concept, the lifetime of BES can be calculated as follows:

$$NL = \frac{H^{LT}}{H^{AT}} \tag{9}$$

where, H^{LT} and H^{AT} are the lifetime energy and the annual energy throughputs, respectively.

Another assumption was that initial and final energy levels of BES are equal within the daily planning period. Therefore, the daily energy constraint can be represented as:

$$E_{t=0} = E_{t=T} \tag{10a}$$

$$\sum_{t=1}^{T}\left(\Delta E_t^{E,ch}.(1-U_t)+\sum_{j=1}^{J}\Delta E_{t,j}^{DR}.(1-\upsilon_{t,j})\right)=\sum_{t=1}^{T}\left(\Delta E_t^{E,dch}.U_t+\sum_{j=1}^{J}\Delta E_{t,j}^{UR}.\upsilon_{t,j}\right) \tag{10b}$$

$$\sum_{t=1}^{T}\left(\Delta E_t^{E,ch}-A_t^{E}+\sum_{j=1}^{J}\left(\Delta E_{t,j}^{DR}-A_{t,j}^{RS}\right)\right)=0:\mu^{1} \tag{10c}$$

Hence, the annual throughput energy or delivered energy can be calculated as:

$$H^{AT}=W.\sum_{t=1}^{T}\left(\Delta E_t^{E,dch}.U_t+\sum_{j=1}^{J}\left(\Delta E_{t,j}^{UR}.\upsilon_{t,j}\right)\right) \tag{11a}$$

$$H^{AT}=W.\sum_{t=1}^{T}\left(A_t^{EAT}+\sum_{j=1}^{J}A_{t,j}^{RAT}\right):\mu^{2} \tag{11b}$$

$$A_t^{EAT}\le M^{AT}.U_t\ :\ \lambda_t^{10},\forall t,\forall j \tag{11c}$$

$$A_{t,j}^{RAT}\le M^{AT}.\upsilon_{t,j}\ :\ \lambda_{t,j}^{11},\forall t,\forall j \tag{11d}$$

$$A_t^{EAT}\le \Delta E_t^{E,dch}\ :\ \lambda_t^{12},\forall t,\forall j \tag{11e}$$

$$A_{t,j}^{RAT}\le \Delta E_{t,j}^{UR}\ :\ \lambda_{t,j}^{13},\forall t,\forall j \tag{11f}$$

$$A_t^{EAT}\ge \Delta E_t^{E,dch}-M^{AT}.(1-U_t):\ \lambda_t^{14},\forall t,\forall j \tag{11g}$$

$$A_{t,j}^{RAT} \geq \Delta E_{t,j}^{UR} - M^{AT}.(1-\upsilon_{t,j}) : \lambda_{t,j}^{15}, \forall t, \forall j \tag{11h}$$

$$A_{t}^{EAT}, A_{t,j}^{RAT} \geq 0 : \forall t, \forall j \tag{11i}$$

where, W is average working days per year as the daily optimal scheduling of BES was calculated and then extend to the whole period.

The main operational constraints of BES are capacity and ramp-rate. The stored energy of BES can be represented as follows:

$$\begin{aligned} E_{t,j} &= E_{t,j-1} + \left(S_{t,j} - S_{t,j-1}\right).\Delta E_t^{E} + \Delta E_{t,j}^{RS} \\ &= E_{t,j-1} + (S_{t,j} - S_{t,j-1}).(\Delta E_t^{E,ch} - A_t^{E}) + \Delta E_{t,j}^{DR} - A_{t,j}^{RS} \end{aligned} \quad : \forall t,\ \forall j \tag{12}$$

where, the term $S_{t,j} - S_{t,j-1}$ represents the duration of intra-hourly time step. The maximum and minimum capacity limitations of BES are represented by (13a) and (13b), respectively. Moreover, the annual degradation of BES capacity is modelled by (13c).

$$E_{t,j} \leq E_l^{Rated} : \lambda_{t,j}^{16}, \forall t,\ \forall j \tag{13a}$$

$$E^{\min} \leq E_{t,j} : \lambda_{t,j}^{17}, \forall t,\ \forall j \tag{13b}$$

$$E_l^{Rated} = E_{l-1}^{Rated}(1-\psi.l) : \forall l = 1, \ldots, NL \tag{13c}$$

In addition, charging and discharging ramp-rate constraints are represented by (14a) and (14b), respectively.

$$\Delta E_t^{E,ch} - A_t^{E} + \frac{\Delta E_{t,j}^{DR} - A_{t,j}^{RS}}{S_{t,j} - S_{t,j-1}} \leq RR^{Ch} : \lambda_{t,j}^{18}, \forall t,\ \forall j \tag{14a}$$

$$A_t^{E} - \Delta E_t^{E,ch} - \frac{\Delta E_{t,j}^{DR} - A_{t,j}^{RS}}{S_{t,j} - S_{t,j-1}} \leq RR^{Dch} : \lambda_{t,j}^{19}, \forall t,\ \forall j \tag{14b}$$

According to the presented payment functions, the deterministic objective function or overall profit can be written as follows:

$$\begin{aligned} & Max\ \ W.\frac{1-(1+r)^{-NL}}{r}\left(\sum_{t=1}^{T} A_t^{PE} - \pi_t^{BE}.\Delta E_t^{E,ch} + \sum_{j=1}^{J}(\pi_{t,j}^{DR} - \pi_{t,j}^{CH}).\Delta E_{t,j}^{DR} - A_{t,j}^{DR} + A_{t,j}^{UR}\right) \\ & s.t.: (1c)-(1e),(2c)-(2e),(4b)-(4d),(7b)-(7g),(10c),(11b)-(11h),(13), and\,(14). \\ & \quad \Delta E_t^{E,ch}, \Delta E_t^{E,dch}, A_t^{E}, A_t^{PE}, A_t^{EAT}, \Delta E_{t,j}^{DR}, \Delta E_{t,j}^{UR}, A_{t,j}^{RS}, A_{t,j}^{DR}, A_{t,j}^{UR}, A_{t,j}^{RAT} \geq 0 : \forall t,\ \forall j \\ & \quad U_t, \upsilon_{t,j} \in [0,1] : \forall t,\ \forall j \end{aligned} \tag{15}$$

As mentioned before, the prices of energy, participation in the regulation service, deployment in real-time market and charging (π_t^{SE}, π_t^{BE}, $\pi_{t,j}^{DR}$, $\pi_{t,j}^{UR}$, $\pi_{t,j}^{RT}$ and $\pi_{t,j}^{CH}$) are considered as the uncertainty resources. The realizations of uncertain parameters or confidence intervals are represented by (16).

$$-\varepsilon^{SE}.\pi_t^{SE} \le \delta_t^{SE} \le \varepsilon^{SE}.\pi_t^{SE} : \forall t \tag{16a}$$

$$-\varepsilon^{BE}.\pi_t^{BE} \le \delta_t^{BE} \le \varepsilon^{BE}.\pi_t^{BE} : \forall t \tag{16b}$$

$$-\varepsilon^{DR}.\pi_{t,j}^{DR} \le \delta_{t,j}^{DR} \le \varepsilon^{DR}.\pi_{t,j}^{DR} : \forall t,\ \forall j \tag{16c}$$

$$-\varepsilon^{UR}.\pi_{t,j}^{UR} \le \delta_{t,j}^{UR} \le \varepsilon^{UR}.\pi_{t,j}^{UR} : \forall t,\ \forall j \tag{16d}$$

$$-\varepsilon^{CH}.\pi_{t,j}^{CH} \le \delta_{t,j}^{CH} \le \varepsilon^{CH}.\pi_{t,j}^{CH} : \forall t,\ \forall j \tag{16e}$$

$$-\varepsilon^{RT}.\pi_{t,j}^{RT} \le \delta_{t,j}^{RT} \le \varepsilon^{RT}.\pi_{t,j}^{RT} : \forall t,\ \forall j \tag{16f}$$

$$0 \le \varepsilon^{SE}, \varepsilon^{BE}, \varepsilon^{DR}, \varepsilon^{UR}, \varepsilon^{CH}, \varepsilon^{RT} \le 1 \tag{16g}$$

According to the concept of Robust Optimization (see [46]), when taking into account the confidence intervals (16), objective function (15) can be reformulated as follows:

$$Max\, Min\ W.\frac{1-(1+r)^{-NL}}{r}\left(\begin{array}{l}\sum_{t=1}^{T} A_t^{PE} - (\pi_t^{BE}+\delta_t^{BE}).\Delta E_t^{E,ch} \\ +\sum_{j=1}^{J}(\pi_{t,j}^{DR}+\delta_{t,j}^{DR}-\pi_{t,j}^{CH}-\delta_{t,j}^{CH}).\Delta E_{t,j}^{DR} - A_{t,j}^{DR} + A_{t,j}^{UR}\end{array}\right)$$

$$s.t.: (1c)-(1e),(2c),(4b)-(4d),(7b)-(7c),(10c),(11b)-(11h),(13), and\,(14). \tag{17a}$$

$$A_t^{PE} \le (\pi_t^{SE}+\delta_t^{SE}).\Delta E_t^{E,dch} + (\pi_t^{BE}+\delta_t^{BE}).\Delta E_t^{E,ch} : \forall t \tag{17b}$$

$$A_t^{PE} \ge (\pi_t^{SE}+\delta_t^{SE}).\Delta E_t^{E,dch} + (\pi_t^{BE}+\delta_t^{BE}).\Delta E_t^{E,ch} - M^{PE}.(1-U_t) : \forall t \tag{17c}$$

$$A_{t,j}^{DR} \le \left(\pi_{t,j}^{CH}+\delta_{t,j}^{CH}-\pi_{t,j}^{DR}-\delta_{t,j}^{DR}\right).\Delta E_{t,j}^{DR} :\ \forall t,\ \forall j \tag{17d}$$

$$A_{t,j}^{UR} \le \left(\pi_{t,j}^{UR}+\delta_{t,j}^{UR}+\pi_{t,j}^{RT}+\delta_{t,j}^{RT}\right).\Delta E_{t,j}^{DR} :\ \forall t,\ \forall j \tag{17e}$$

$$A_{t,j}^{DR} \ge \left(\pi_{t,j}^{CH}+\delta_{t,j}^{CH}-\pi_{t,j}^{DR}-\delta_{t,j}^{DR}\right).\Delta E_{t,j}^{DR} - M^{RG}.(1-\upsilon_{t,j}) :\ \forall t,\ \forall j \tag{17f}$$

$$A_{t,j}^{UR} \ge \left(\pi_{t,j}^{UR}+\delta_{t,j}^{UR}+\pi_{t,j}^{RT}+\delta_{t,j}^{RT}\right).\Delta E_{t,j}^{DR} - M^{RG}.(1-\upsilon_{t,j}) :\ \forall t,\ \forall j \tag{17g}$$

Considering that (2d)-(2e) and (7d)-(7g) depend on the uncertainty parameters and that in (15) uncertainty was not considered, (2d)-(2e) and (7d)-(7g) were replaced by (17b)-(17g).

In the presented objective function, the lower bound of minimization is achieved for the minimum selling prices (π_t^{SE}, $\pi_{t,j}^{DR}$, $\pi_{t,j}^{UR}$, and $\pi_{t,j}^{RT}$) and maximum buying and charging prices (π_t^{BE} and $\pi_{t,j}^{CH}$). Therefore, the worst-case realizations of uncertain parameters within the variation interval are as follows:

$$\delta_t^{SE} = -\varepsilon^{SE}.\pi_t^{SE}; \forall t \tag{18a}$$

$$\delta_t^{BE} = \varepsilon^{BE}.\pi_t^{BE}; \forall t \tag{18b}$$

$$\delta_{t,j}^{DR} = -\varepsilon^{DR}.\pi_{t,j}^{DR}; \forall t, \forall j \tag{18c}$$

$$\delta_{t,j}^{UR} = -\varepsilon^{UR}.\pi_{t,j}^{UR}; \forall t, \forall j \tag{18d}$$

$$\delta_{t,j}^{CH} = \varepsilon^{CH}.\pi_{t,j}^{CH}; \forall t, \forall j \tag{18e}$$

$$\delta_{t,j}^{RT} = -\varepsilon^{RT}.\pi_{t,j}^{RT}; \forall t, \forall j \tag{18f}$$

Accordingly, the Max-Min problem (17) can be converted to the Max optimization problem, as follows:

$$Max \;\; W.\frac{1-(1+r)^{-NL}}{r}\left(\begin{array}{l} \sum\limits_{t=1}^{T} A_t^{PE} - (\pi_t^{BE} + \varepsilon^{BE}.\pi_t^{BE}).\Delta E_t^{E,ch} \\ \sum\limits_{j=1}^{J} \left(\pi_{t,j}^{DR} - \varepsilon^{DR}.\pi_{t,j}^{DR} - \pi_{t,j}^{CH} - \varepsilon^{CH}.\pi_{t,j}^{CH}\right).\Delta E_{t,j}^{DR} - A_{t,j}^{DR} + A_{t,j}^{UR} \end{array}\right)$$

$$s.t.: (1c)-(1e),(2c),(4b)-(4d),(7b)-(7c),(10c),(11b)-(11h),(13), and\,(14). \tag{19a}$$

$$A_t^{PE} \le \pi_t^{SE}.(1-\varepsilon^{SE}).\Delta E_t^{E,dch} + \pi_t^{BE}.(1+\varepsilon^{BE}).\Delta E_t^{E,ch} \; : \lambda_t^{20}, \forall t \tag{19b}$$

$$A_t^{PE} \ge \pi_t^{SE}.(1-\varepsilon^{SE}).\Delta E_t^{E,dch} + \pi_t^{BE}.(1+\varepsilon^{BE}).\Delta E_t^{E,ch} - M^{PE}.(1-U_t) \; : \lambda_t^{21}, \forall t \tag{19c}$$

$$A_{t,j}^{DR} \le \left(\pi_{t,j}^{CH}.(1+\varepsilon^{CH}) - \pi_{t,j}^{DR}.(1-\varepsilon^{DR})\right).\Delta E_{t,j}^{DR} : \; \lambda_{t,j}^{22}, \forall t, \forall j \tag{19d}$$

$$A_{t,j}^{UR} \le \left(\pi_{t,j}^{UR}.(1-\varepsilon^{UR}) + \pi_{t,j}^{RT}.(1-\varepsilon^{RT})\right).\Delta E_{t,j}^{UR} : \; \lambda_{t,j}^{23}, \forall t, \forall j \tag{19e}$$

$$A_{t,j}^{DR} \ge \left(\pi_{t,j}^{CH}.(1+\varepsilon^{CH}) - \pi_{t,j}^{DR}.(1-\varepsilon^{DR})\right).\Delta E_{t,j}^{DR} - M^{RG}.(1-\upsilon_{t,j}) : \; \lambda_{t,j}^{24}, \forall t, \forall j \tag{19f}$$

$$A_{t,j}^{UR} \ge \left(\pi_{t,j}^{UR}.(1-\varepsilon^{UR}) + \pi_{t,j}^{RT}.(1-\varepsilon^{RT})\right).\Delta E_{t,j}^{UR} - M^{RG}.(1-\upsilon_{t,j}) : \; \lambda_{t,j}^{25}, \forall t, \forall j \tag{19g}$$

3.3.3. RESTrade

Most of the European electricity markets encompass the aFRR capacity market. This market closes at the day *D,* and requires the forecast of the maximum consumption and the expected production from traditional dispatchable power plants and vRES, computing the hourly capacity aFRR requirements for the next day (D+1). Furthermore, all producers with technical capability submit capacity bids for the next 24 hours of the next day (*D*+1). All players (supplier and consumer) participate under the same rules, whether they are conventional energy source producers and easily controlled, or if they are producers who use stochastic sources, such as the wind and solar (photovoltaic) energy.

To participate in this market, numerical weather prediction models (NWP) like the Fifth-generation model (also known as MM5 [48]) are used by most of the players [49]. Notwithstanding the developments observed in the physical parameterizations of these models as well as the initial and boundary conditions (IBC), systematic errors (phase and amplitude) still persist due to the chaotic nature of the atmosphere, in which small (initial) errors necessarily grow in the deterministic chaotic system and eventually result in the deterioration of the forecast for a long time horizon [50] (Figure 16).

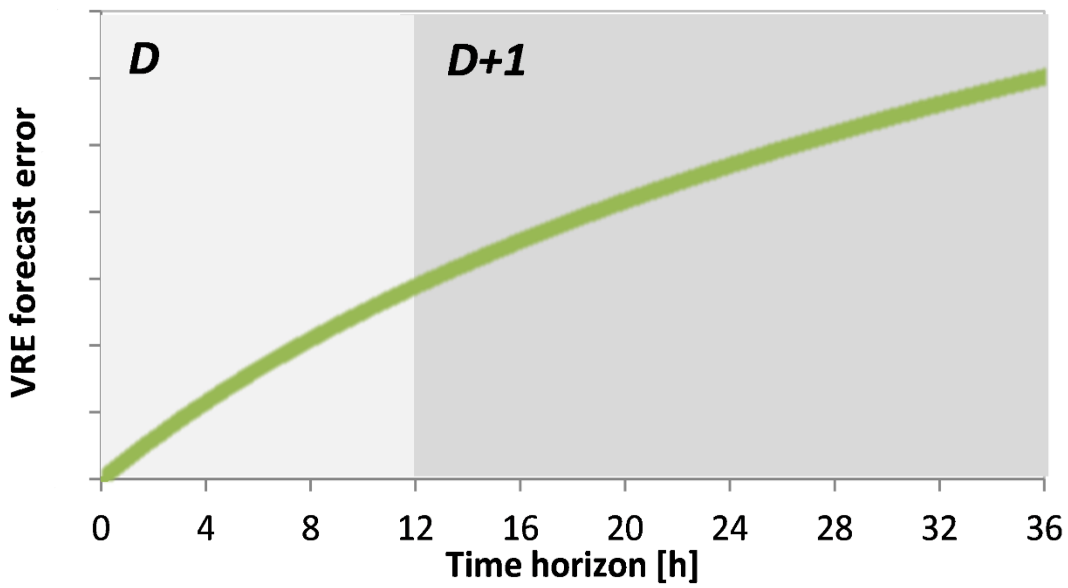

Figure 16: Illustration of the increase of the wind forecast error over a the time horizon of 36 hours; adapted from: [47]

One of the main limiting factors of NWP accuracy are the IBC used by the mesoscale models [52, 53]. These models use the Navier-Stokes equations resulting to physical parameterizations and the IBC data [48]. Mesoscale models have the ability to describe the behaviour and evolution of air masses and treat explicitly the inherent phenomena of atmospheric turbulence and stratification as well as other types of nonlinear atmospheric phenomena, up to a maximum spatial resolution of 1×1km [53]. For forecast application, these IBC data are typically available from global models like the Global Forecast System (GFS) [54], at 00, 06, 12, and 18 UTC. Currently, to participate in the day-ahead market, producers need to use the IBC from 06 UTC, representing a time gap of 18 hours interval between the forecast and the first delivery hour (Figure 17).

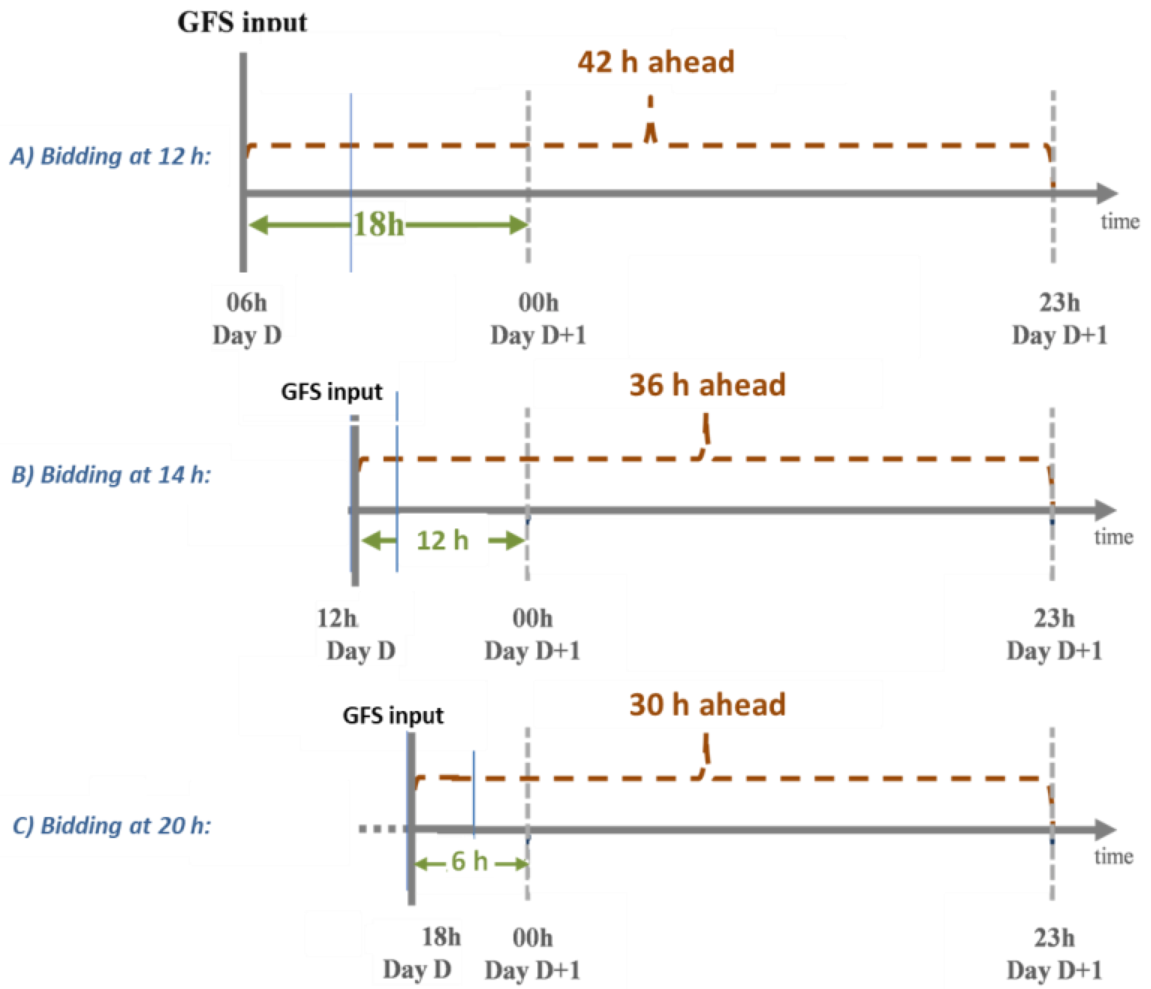

Figure 17: Timeframes for day-ahead market:A) current design; B) and C) proposed designs; adapted from [51]

For wind power, some authors, e.g. [8], showed that reducing this gap can enable increasing this technology's value in the day-ahead market due to a significant reduction in the forecast errors leading to a reduction in the flexibility needed. The same is true when allowing this technology to effectively participate in the balancing markets. The main motivation for reducing the time gap is closely related to the IBC data availability. Particularly, the motivation is exploring the benefit of using the 12 and 18 UTC data available from global models to feed the power forecast systems in an electricity market environment. An additional period of two hours is considered to run the models and perform all required steps to obtain the forecast/bids. Thus, the new gate closure should be at 14 UTC and 20 UTC.

In TradeRES project, the certainty gain effect [51] of using close to real time IBC data will be assessed and extended to other vRES players and to the demand-side. Therefore, the following specifications of the balancing markets are going to be applied within the project:

- *Rolling gate closures:* Instead of a single day-ahead aFRR capacity market, considering several hourly or 15-minutes trades during the day can be beneficial to improve the aFRR capacity procurement and to enable an effective participation of vRES in the balancing markets avoiding large quantities of deviations and energy curtailments;
- *Variable market closures lead time:* The procurement of aFRR capacity depends on the forecasts of the maximum expected consumption and vRES productions, so shorter lead times between bidding and delivery of capacity can improve the aFRR requirements, increasing its efficient use. In the case of mFRR energy markets, shorter lead time between bidding and delivery of energy may enable an efficient participation of vRES in these markets, contributing to reduce the vRES deviations and/or curtailments.

4. Conclusion

This report describes implementations of temporal flexibility options that either i) were available in the agent-based electricity market models AMIRIS, MASCEM or RESTrade prior to the start of the research project TradeRES or ii) were implemented within the course of the TradeRES project. Other reports focussing on sectoral or spatial flexibility options accompany this document.

The ability to "Trade with shorter time units" was available in all considered models before the start of the project. Representations of further temporal flexibility options like

- Load shedding,
- Electricity storage,
- Rolling market clearing,
- Real-time pricing and,
- Variable market closure lead times

were also already available in some of the models. Those aspects were introduced to some ABM of TradeRES not yet having those modelling capabilities. In addition, some existing implementations were enhanced during the course of the project. "Load shifting" was not implemented in any of the considered ABM models before the start of TradeRES and was now introduced to MASCEM and AMIRIS.

Details of all feature implementations in the respective ABMs were explained thoroughly in the previous chapter. The selection of temporal flexibility options to implement was made with regard to a predominantly temporal characteristic, a contribution to TradeRES' assessment of market designs, and the feasibility to be implemented in at least one of the ABMs during the project's lifetime. The choices follow the capabilities of each model and aim to fully utilise the joint model suite to be developed also in this work package of TradeRES (see also [55]). Albeit there is no additional report planned to discuss further model improvements, some of the mentioned features might be further extended or improved over the course of the project. Other temporal flexibility options not yet considered might also be integrated if they facilitate the assessment of market designs or are requested by stakeholders participating in the project, provided resources allow to do so.

The implementations of the temporal flexibility options will be necessary for the model-based analyses within the case studies of TradeRES Work Package 5. There, the role of different flexibility options and the impacts of different market designs to address the main objectives of a future European energy system will be studied. To enable a joint assessment of the different flexibility options and to consider short-term decisions along with long-term investments, the TradeRES models will be coupled in Task 4.3 of Work Package 4. This endeavour will lead to an open-access market simulation toolbox comprising many different assessment possibilities that can be used for comprehensive market design studies.

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