A Bidding Algorithm for the Joint Participation of Distributed Energy Resources in Day-Ahead Energy and mFRR markets

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***Abstract*—This paper provides an optimization algorithm for the joint participation of an aggregator of flexible demand in the day-ahead (DA) energy and manual frequency response (mFRR) markets. The algorithm, which is based on a mixed integer linear (MILP) optimization problem, defines the bids to be sent to the aforementioned markets, with the aim of minimizing the net cost for buying and selling energy in the DA market while maximizing the benefits from its participation in the mFRR market. This combined bidding strategy helps the aggregator to perform a better schedule of its flexibility resources, thus improving its revenue opportunities. The proposed bidding algorithm is tested in a realistic simulation case study based on the Portuguese pilot within the ELEXIA project comprising three office climatization systems and a photovoltaic generator. Results demonstrate the applicability of the developed algorithm to estimate the available flexibility and define the optimal multi-market bidding strategy.**

***Index Terms*-- aggregator, demand-side response, optimization, distributed energy resources, flexibility markets.**

I. INTRODUCTION

The electricity sector is moving towards a scenario with high penetration of renewable energy connected at the distribution networks, as well as the electrification of end-uses traditionally linked to fossil fuels (e.g., heat pumps, electric vehicles). This represents a challenge for transmission and distribution system operators (TSOs and DSOs) that need higher amounts of flexibility to operate their networks and therefore maintain system stability. In this context, distributed energy resources (DERs) –flexible demand, distributed generation, electric energy storage systems– can play a crucial role in supporting system operators by participating in flexibility markets. These include conventional balancing markets operated by TSOs, as well as new emerging local flexibility markets at the distribution level operated by DSOs. To facilitate this, the existence of an aggregator responsible for managing the capacity of small and medium-scale DERs (below 1 MW) and mediating between them and the flexibility markets is necessary [1],[2].

This paper provides a tool for an aggregator to define the bidding strategy for the joint participation in the Day-Ahead (DA) energy [3] and manual Frequency Restoration Reserve (mFRR) markets [4]. The developed bidding algorithm is based on a mixed integer linear programming (MILP) optimization model aimed at minimizing the net cost for buying and selling energy in the DA market while maximizing the benefits from its participation in the mFRR market. Prosumers' comfort preferences and technical constraints of the controlled devices are also included within the algorithm. As output, the model determines the bids to be submitted to the aforementioned markets, as well as the individual control actions to be applied to the DERs, based on a direct load control (DLC) scheme. The main advantage of the developed algorithm is that it defines the bidding strategy for both markets simultaneously. In this way, the aggregator can better schedule the flexibility provided by the resources in its portfolio (e.g., by reserving part of their capacity to the mFRR market) and, therefore, maximize its revenues in comparison to a single participation in DA market.

The work presented in this paper takes as starting point the market participation algorithms presented in [5]-[13] to develop a bidding strategy to be applied to the Portuguese pilot in the European research project ELEXIA [14]. The flexibility resources include three office heat, ventilation and air-conditioning systems (HVACs) and a photovoltaic (PV) generator. The objective of the case study is to estimate the bids that an aggregator could potentially offer in the DA energy and mFRR flexibility markets for a particular simulation scenario and demonstrate that the combined participation in both markets can increase the expected profit of the aggregator in relation to a single participation in DA energy markets.

The paper is divided into five main sections. Section I is the introduction. Section II describes the developed multi-market bidding algorithm. Section III presents the considered case study. Section IV shows the results of the application of the developed model to the case study. Finally, Section V summarizes the main conclusions drawn from the study and the future work to be done.

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II. MULTI-MARKET BIDDING ALGORITHM

This section presents the mathematical formulation of the developed multi-market bidding algorithm for the joint participation in the DA energy and the mFRR balancing markets.

A. Electricity market framework

The DA market is operated by the market operator (OMIE for Spain and Portugal [3]) and it is aimed at managing the energy transactions among demand and supply agents. Participating players can submit electricity sale/purchase bids for every hour of the following day D before market gate closure, occurring at 12:00 p.m. of the day D-1. There is a single DA market session per day, all year round, which sets the quantities and prices of electricity for all hours of the next day. The pricing mechanism follows a pay-as-clear approach, meaning that all participating agents buy and sell energy at the clearing price calculated as the intersection between supply and demand curves.

The mFRR service is activated by the TSO (REE in Spain [4],[15], REN in Portugal [18]) when needed to solve system imbalances and restore the secondary reserve used. This service is managed thorough market mechanisms, where participating agents can send bids about their available capacity for upwards or downwards regulation for each 15-min time period of the next day, along with a price for such flexibility. mFRR bids can be submitted between 21:00 and 23:00 the day before delivery, just after the TSO has published their tertiary reserve requirements for the next day. The mFRR bids can afterwards be updated until 25 minutes before the delivery time (H-25) during the intraday period. Participating agents are not paid for reserve capacity, they are only compensated for the actual activation made by the TSO. To decide final assignments, a mFRR market clearing process is conducted every 15-minute time-period of the day. Nowadays, the mFRR service is integrated into the European mFRR platform MARI [19].

In this context, the aggregator acts as a buyer and seller of electricity by sending bids to the DA and mFRR markets. In a conventional scenario, the trading process would be sequential, that is, the aggregator would first send bids to the DA market. After DA market is cleared by the market operator and prices and commitments are published, the aggregator would send the bids for the mFRR markets including the remaining available capacity. In this paper a multi-market bidding approach is developed. In this case, the decision-making process is carried out the day before, taking into account the joint participation of the aggregator in DA and mFRR services. By doing this, the aggregator can potentially increase its profits as it can reserve part of the available flexibility to the mFRR markets in case they are expected to be more profitable than the DA market. The aggregator acts as a price-taker by sending non-priced bids to the markets [7].

It should be noted that the developed algorithm assists the aggregator in the day-ahead bidding phase. During the intra-day period, it will be necessary to update the mFRR bids, taking into account more recent forecasts of the mFRR market prices and other variables such as prosumers' behavior, climate conditions, as well as firm schedules from previous markets. This is out of the scope of this paper.

B. Optimization algorithm formulation

The input parameters and decision variables involved in the optimization problem are listed below:

Sets and indexes

T	set of indexes t of time periods
D	set of indexes d for demand flexibility resources
S	set of indexes s for supply flexibility resources

Parameters

Δt	time-step duration [h]
λ_t^{DA}	forecasted energy price in the DA market at time-step t [€/kWh]
λ_t^{UR}	forecasted price for the activation of upward mFRR at the time-step t [€/kWh]
λ_t^{DR}	forecasted price for the activation of downward mFRR at the time-step t [€/kWh]
$P_t^{max,d}$	maximum power of the demand resource d at time-step t [kW]
$P_t^{max,s}$	maximum power of the supply resource s at time-step t [kW]
ρ_t^{UR}	estimated activation percentage of the offered flexibility in the Upward mFRR market at time-step t [%]
ρ_t^{DR}	estimated activation percentage of the offered flexibility in the Downward mFRR market at time-step t [%]

Optimization variables

P_t^{tot}	net power of the aggregator at time-step t [kW]
P_t^{DA}	net power of the aggregator at the DA market at time-step t [kW]. The value of $(P_t^{DA} \cdot \Delta t)$[kWh] represents the energy bids at the DA market
P_t^{UR}	net power of the aggregator at the Upward mFRR market at time-step t [kW]
P_t^{DR}	net power of the aggregator at the Downward mFRR market at time-step t [kW]
P_t^{d}	total power consumption of the demand resource d at time-step t [kW]
$P_t^{DA,d}$	total power of the demand resource d at the DA market at time-step t [kW].
$P_t^{UR,d}$	total power of the demand resource d at the Upward mFRR market at time-step t [kW].
$P_t^{DR,d}$	total power of the demand resource d at the Downward mFRR market at time-step t [kW].
P_t^{s}	total power generation of the supply resource s at time-step t [kW]

$P_t^{DA,s}$ total power of the supply resource s at the DA market at time-step t [kW].

$P_t^{UR,s}$ total power of the supply resource s at the Upward mFRR market at time-step t [kW].

$P_t^{DR,s}$ total power of the supply resource s at the Downward mFRR market at time-step t [kW].

The objective of the optimization algorithm is to minimize the net cost of the aggregator for buying and selling energy in the DA market while maximizing the benefits from its participation in the mFRR market over the planning horizon $t \in T$. The objective function, based on a mixed integer linear program (MILP), can be formulated as follows:

$$min \sum_{t=1}^{T} \begin{pmatrix} \lambda_t^{DA} \cdot P_t^{DA} + \lambda_t^{DR} \cdot P_t^{DR} \cdot \rho_t^{DR} \\ -\lambda_t^{UR} \cdot P_t^{UR} \cdot \rho_t^{UR} \end{pmatrix} \cdot \Delta t \qquad (1)$$

The first term in (1) represents the net energy cost for buying energy and selling energy in the DA market. The second and third terms in (1) represent the expected benefits of deploying downward and upward mFRR reserves in the intraday period. Downward reserve implies decreasing power generation or increasing power consumption, which represents a cost for the aggregator. Upward reserve implies increasing power generation or decreasing power consumption, which is translated into a revenue. ρ_t^{UR} and ρ_t^{DR} represent the considered percentage of activation in the intraday phase in relation to the offered flexibility in the upward and downward mFRR markets respectively. Estimation of these parameters is carried out by the aggregator based on historical data of mFRR activations.

The constraints of the optimization problem are the following ones:

1) Aggregated participation in the electricity markets

Constraint (2) represents the final aggregated power of the aggregator taking into account the participation in the different markets. Constraints (3)-(5) define the overall participation of the aggregator in each market which is calculated as the sum of the individual contributions of all demand and generation resources. Note that the adopted sign convention considers power consumption as a positive value and power generation as a negative value. According to this, positive values of P_t^{DA} represent "demand bids" and negative values of such variable "supply bids".

$$P_t^{tot} = P_t^{DA} + P_t^{DR} - P_t^{UR}, \ t \in T \qquad (2)$$

$$P_t^{DA} = \sum_{d=1}^{D} P_t^{DA,d} - \sum_{s=1}^{S} P_t^{DA,s}, \ t \in T \qquad (3)$$

$$P_t^{UR} = \sum_{d=1}^{D} P_t^{UR,d} + \sum_{s=1}^{S} P_t^{UR,s}, \ t \in T \qquad (4)$$

$$P_t^{DR} = \sum_{d=1}^{D} P_t^{DR,d} + \sum_{s=1}^{S} P_t^{DR,s}, \ t \in T \qquad (5)$$

2) Individual participation in electricity markets

Constraints (6) and (7) represent the final power of each individual demand and generation resource respectively taking into account the participation in the different markets. Constraints (8) and (9) set the limits for upward and downward regulation for demand resources based on their participation in the DA market. Finally, constraints (10) and (11) define the limits for upward and downward regulation for supply resources based on the participation in the DA market.

$$P_t^{d} = P_t^{DA,d} + P_t^{DR,d} - P_t^{UR,d}, \ t \in T, d \in D \qquad (6)$$

$$P_t^{s} = P_t^{DA,s} - P_t^{DR,s} + P_t^{UR,s}, \ t \in T, s \in S \qquad (7)$$

$$0 \le P_t^{UR,d} \le P_t^{DA,d}, \ t \in T, d \in D \qquad (8)$$

$$0 \le P_t^{DR,d} \le P^{max,d} - P_t^{DA,d}, \ t \in T, d \in D \qquad (9)$$

$$0 \le P_t^{UR,s} \le P_t^{max,s} - P_t^{DA,s}, \ t \in T, s \in S \qquad (10)$$

$$0 \le P_t^{DR,s} \le P_t^{DA,s}, \ t \in T, s \in S \qquad (11)$$

3) Physical models of the energy resources

Additional constraints defining the physical models of the energy resources should be included. These will impose the technical and user-defined comfort limitations when calculating P_t^d y P_t^s respectively [5],[10]. In this paper, HVAC systems as demand resources and PV generators as supply resources are considered. Detailed formulation of these models is provided in Appendix A.

III. Case Study

To test the performance of the developed bidding algorithm, a simulation case study based on the Portuguese pilot of the ELEXIA project [14] has been considered. It is located at the Port of Sines (Portugal) and the technologies available that can provide flexibility are the following ones: 3 office buildings with HVACs and 1 PV generator. The characteristics of each flexible resource are presented in Table I (see Appendix A for nomenclature description).

TABLE I. DER parameters for the case study

DERs	
Type	***Parameters***
HVAC1	htc = 20 kW/ºC, hcc = 0.007 ºC/kWh, Pmax = 88 kW, η= 3.69, Tªmax = 25 ºC, Tªmin = 21 ºC, Tªini = 23 ºC, tini = 8 h , tend=18 h
HVAC2	htc = 15 kW/ºC, hcc = 0.009 ºC/kWh, Pmax = 59 kW, η = 3.6, Tªmax = 25 ºC, Tªmin = 21 ºC, Tªini = 23 ºC, , tini = 8 h , tend = 18 h
HVAC3	htc =80 kW/ºC, hcc = 0.004 ºC/kWh, Pmax = 294 kW, η = 3.7, Tªmax = 25 ºC, Tªmin = 21 ºC, Tªini = 23 ºC, , tini = 8 h , tend = 18 h
PV	Pinst = 250 kW, eff = 0.175

It is assumed that there is an aggregator representing the prosumer that implements a DLC scheme over its energy resources. Possible control actions include changes on the temperature set-points for the HVAC systems and active power curtailments for the PV system.

The simulation is conducted for a specific hot summer weekday, 23rd July 2024, during which HVAC systems are acting as cooling systems. According to the market rules, this optimization is carried out the 22nd July 2024 before 12:00 p.m. (DA market gate closure). Previously to the application of the algorithm, the aggregator should estimate DA and mFRR market prices for the next day, as well as weather data. Forecasted outdoor temperature and irradiance for the considered day at the Port of Sines are presented in Fig. 1 [16],[17].

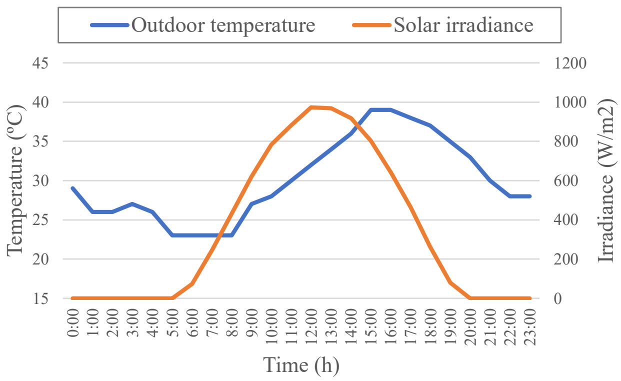

Figure 1. Weather data for the case study

The forecasted prices for the DA energy and the upward and downward mFRR markets are shown in Fig.2. These represent actual data for the considered day obtained from REN website [18].

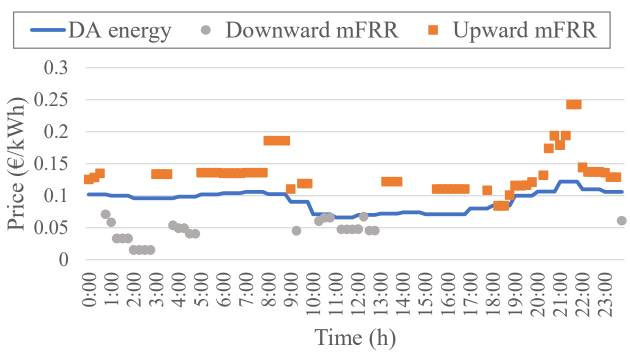

Figure 2. Market prices for the case study

The aim of the case study is to define the optimal bidding strategy of the aggregator for the joint participation in DA and mFRR markets for the considered day. The obtained bidding strategy is compared with a simple bidding approach in which the aggregator only participates in the DA market (baseline scenario).

IV. Results

Fig. 3 shows the baseline scenario results, where a simple bidding approach is used, considering only participation in the DA energy market. HVAC systems operate from 8:00 to 18:00 to keep indoor temperatures between the comfort limits (21ºC and 25ºC), with some flexibility for pre-cooling before high-price periods (e.g., 17:00). This lowers the internal temperature to the minimum comfort level, reducing as a consequence, consumption during high-price periods. The PV plant generates energy based on solar availability. The prosumer's net power profile is shown in Fig. 3 (yellow line), indicating "demand bids" for most of the day, except between 6:00 and 10:00, when PV generation exceeds demand, resulting in "supply bids".

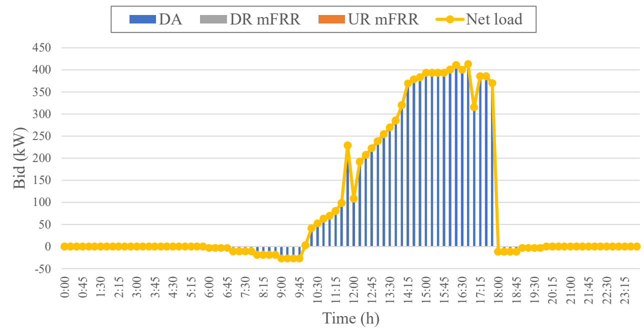

Figure 3. Market bids for the simple bidding scenario (DA -baseline)

Fig. 4 shows the results of applying the developed optimization algorithm to the considered scenario for the joint participation in DA and mFRR markets.

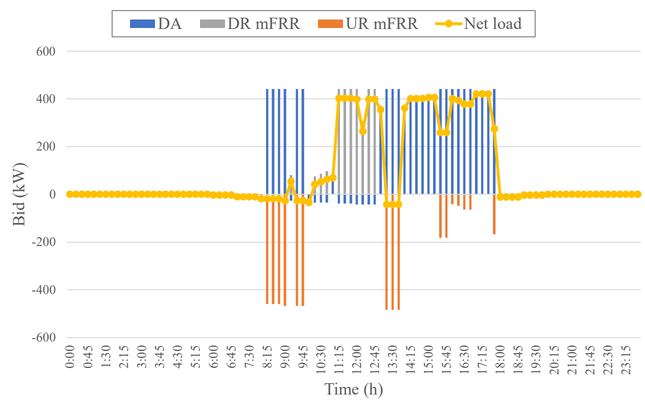

Figure 4. Market bids for the combined bidding scenario (DA+mFRR)

It can be observed that the available flexibility is exploited to maximize the profits when mFRR prices are more profitable than the DA ones. The specific strategies followed by demand and supply resources can be checked in Fig. 5 and Fig. 6 respectively.

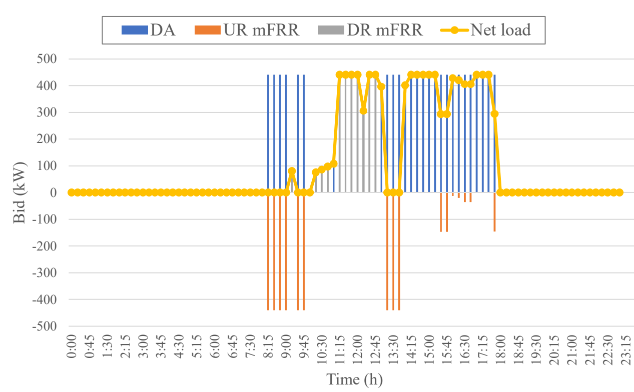

Figure 5. Market bids of demand resources (HVACs)

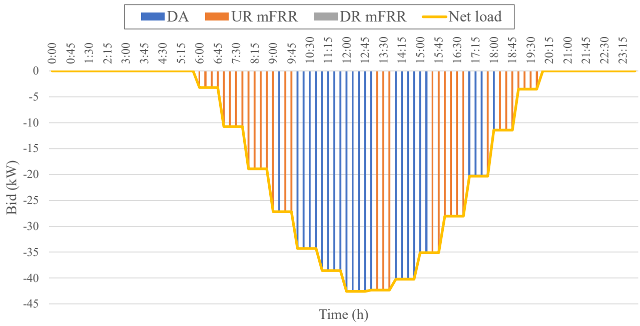

Figure 6. Market bids of generation resource (PV plant)

In Fig.5 it can be observed that demand resources (HVAC systems) bid their maximum available capacity in the DA market during the time periods in which upward mFRR prices are more profitable than DA market prices. The surplus power in relation to their actual power consumption needs, is offered as upward flexibility in the mFRR market (e.g., 8:15-9:15). When downward mFRR prices are more profitable than DA market prices, they allocate their total power consumption needs in the downward mFRR market (e.g., 11:15-12:45). Appendix B includes a plot with the internal temperature variation in both scenarios (DA and DA+mFRR) for HVAC1.

According to the results in Fig. 6, supply resources (PV plant) only participate in the upward mFRR market, as it is not worthwhile for them to curtail generation to provide downward flexibility in this case study because downward mFRR prices are lower than DA market prices. The strategy involves allocating its overall power generation capacity to bid in the upward mFRR market when prices corresponding to this market exceed DA prices (e.g., 06:00 to 10:00).

Fig. 8 shows the total amount of energy traded in each market in each scenario. It can be checked that in the combined participation scenario there is high amount of energy traded in the markets in comparison to the baseline scenario (simple bidding approach). This is due to the use of the available flexibility to make profit in upward and downward mFRR markets.

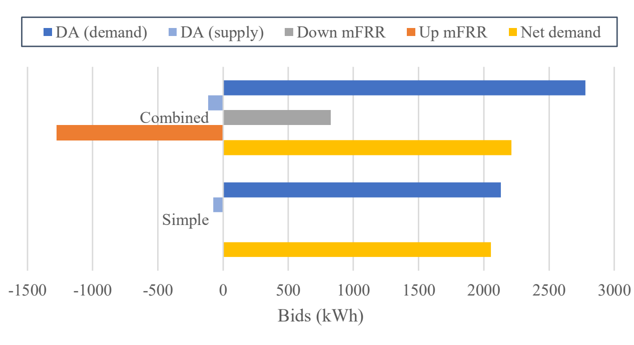

Figure 7. Net amout of energy bid in each market for each scenario

The overall costs for the aggregator in each scenario are presented Table II. It can be checked that the combined strategy reduces the costs of the aggregator from 147.7€ to 78.98€, that is, they are reduced in a 46 %. It has to be noted that these results correspond to an ideal scenario in which forecast information is assumed to be certain. This demonstrates the effectiveness of the developed algorithm to improve the bidding strategy of the aggregator.

TABLE II. AGGREGATOR'S COSTS IN EACH SCENARIO

Scenario	DA	mFRR (UR)	mFRR (DR)	Net cost
Simple	147.7	0	0	147.70
Combined	211.35	-173.51	41.14	78.98

V. CONCLUSIONS AND FUTURE WORK

In this paper, an optimization algorithm for an aggregator of flexible energy resources to define the joint bidding strategy in the day-ahead (DA) and in manual frequency restoration reserve (mFRR) markets has been developed. The algorithm, which is based on a mixed integer linear programming (MILP) model, is aimed at minimizing the net cost for buying and selling energy in the DA market while maximizing the benefits from its participation in the mFRR market.

The algorithm has been applied to a simulation case study, based on data from the Portuguese pilot of the European research project ELEXIA [14] to demonstrate its applicability. From the results of the simulations, it can be concluded that the developed algorithm enables the participation of an aggregator in mFRR markets in combination with the DA market, increasing as a consequence, its expected profits in relation to a single participation in DA markets.

Future work will compare these results with a scenario based on a conventional sequential bidding approach, where decisions for one market are made after the previous market has been closed. This comparison aims to demonstrate that the developed algorithm enables the aggregator to better schedule the flexibility provided by the resources in its portfolio (e.g., by reserving part of their capacity to the mFRR market) thereby, maximizing its revenues.

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APPENDIX A

Formulation of the physical model for a HVAC system:

Parameters

hcc^d heat capacity coefficient of the HVAC *d* [kW/ºC]

htc^d heat transfer coefficient of the HVAC *d* [ºC/kWh]

η^d efficiency (EER/COP) of the HVAC *d*

T_t^{ext} forecasted outdoor temperature at time-step *t* [ºC]

$T_t^{max,d}$ maximum limit for the temperature of HVAC *d* at time-step *t* [ºC]

$T_t^{min,d}$ minimum limit for the temperature of HVAC *d* at time-step *t* [ºC]

T_{ini}^d initial temperature of HVAC *d* [ºC]

$P_t^{max,d}$ maximum power of HVAC *d* at time-step *t* [kW]

$P_t^{min,k}$ minimum power of HVAC *d* at time-step *t* [kW]

Optimization variables

P_t^d total power consumption of the HVAC *d* at time-step *t* [kW]

T_t^d room internal temperature due to the HVAC *d* at time-step *t* [kW]

Formulation

$$T_{t+1}^d + (htc^d \cdot hcc^d \cdot \Delta t - 1) \cdot T_t^d + hcc^d \cdot \Delta t \cdot \eta^d \cdot P_t^d = htc^d \cdot hcc^d \cdot \Delta t \cdot T_t^{ext}, \quad t \in T, d \in D \tag{12}$$

$$T_1^d = T_{ini,}^d \; d \in D \tag{13}$$

$$T_t^{min,d} \le T_t^d \le T_t^{max,d}, \quad t \in T, d \in D \tag{14}$$

$$P_t^{min,d} \le P_t^d \le P_t^{max,d}, \quad t \in T, d \in D \tag{15}$$

Constraint. (12) is a thermal balance defining the internal temperature variation in the room as a function of the HVAC *d* power consumption for each time step *t*. Constraint (13) sets the initial value of the indoor temperature. Constraints (14) and (15) define the limits for the internal temperature and power consumption variables.

Formulation of the physical model for a PV system:

Parameters

$P^{inst,s}$ installed power of PV generator *s* [kW]

eff^s global efficiency of PV generator *s*

A^s installed area of PV generator *s* [m^2]

I_t solar irradiance at time-step *t* [kW/m^2]

Optimization variables

P_t^s total power generation of the PV generator *s* at time-step *t* [kW]

Formulation

$$P_t^s \le P_t^{inst,s} \cdot A^s \cdot eff^s \cdot I_t, \qquad t \in T, s \in S \tag{16}$$

Constraint (16) defines the power production limits of the PV generator *s* as function of the installed power, efficiency and the available solar energy at each time-step *t*.

APPENDIX B

Fig.8 shows a comparison of the internal temperature variation of the HVAC1 in both scenarios: participation only in DA market (blue line), and combined participation in DA and mFRR markets (orange line). It can be checked that in the second scenario, the internal temperature is controlled between the allowed maximum and minimum limits to achieve the required flexibility for markets participation.

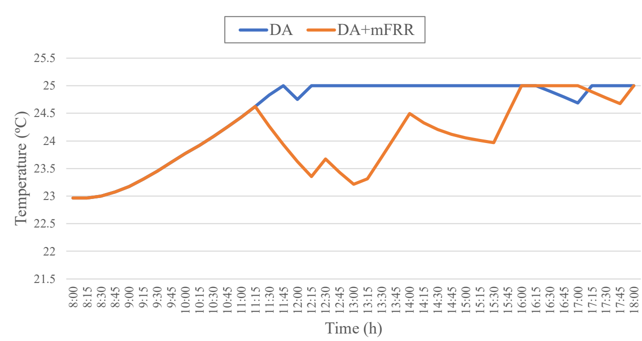

Figure 8. HVAC1 temperature set-points for both scenarios: DA and DA+mFRR