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Integrated Forecasting and Scheduling of Implicit Demand Response in Balancing Markets Using Inverse Optimization

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***Abstract*— Demand Response (DR) programs offer flexibility that is considered to hold significant potential for enhancing power system reliability and promoting the integration of renewable energy sources. Nevertheless, the distributed nature of DR resources presents challenges in developing scalable optimization tools. This paper explores a novel data-driven approach in which DR resources are modeled through their aggregate forecasts using Inverse Optimization. The proposed method utilizes historical price-consumption data to deduce DR price-response behavior via a flexibility curve. The model is assessed within the Belgian single imbalance market context, where a Balance Responsible Party (BRP) employs the inferred flexibility curve to optimize its strategic imbalance positions by managing DR resources through suitable real-time price signals. The accuracy of the estimated flexibility provided by the proposed algorithm is evaluated by comparing it with the XGboost method. The results demonstrate that the model can effectively capture DR behavior and generate profit from providing balancing energy.**

***Index Terms*-- Implicit demand response, Single Imbalance Market, Inverse Optimization, Short-term Forecasting**

NOMENCLATURE

Sets and Indices

$\mathcal{T}$	Set of time steps in study horizon, indexed by t
$\mathcal{B}$	Set of demand response consumption blocks, indexed by b
$\mathcal{M}_t^{TR}$	Set of price-demand scenarios for time t, indexed by s
$\mathcal{R}^{+/-}$	Set of upward (+)/downward (-) regulation bids, indexed by r^+/r^-

Parameters and Constants

λ_t^{DA}	Energy price at time t (€/MWh)
$U_t^{+/-}$	Indicator binary value for system imbalance
P_t^{DA}	Scheduled day-ahead consumption at time t (MW)
$\Lambda_{r^{+/-},t}$	Upward (+)/Downward (-) activation price of reserves of bid r^+/r^- at time t (€/MWh)
$\overline{S}_{r^{+/-},t}$	Maximum upward (+)/downward (-) regulation energy of bid r^+/r^- at time t (MW)
$\widehat{SI}_t$	System Imbalance at time t (MW)
$w_{b,t}$	Willingness-to-pay of DR resources for energy block b at time t (€/MWh)
$\overline{P^{DR}}_t$, $\underline{P^{DR}}_t$	Estimated maximum/minimum power consumption of DR resources at time t (MW)
$E_{b,t}$	The maximum energy of block b at time t (MW)
$P_{t,m}^{DR,Scn}$	DR demand scenarios of time t scenario m (MW)
$\lambda_{t,m}^{DR,Scn}$	Price signal scenarios sent to DR at time t scenario m (€/MWh)
ω_m	Weight of each price-demand scenario m
K	Large positive number

Variables

$\Delta p_t^{imb+/-}$	Upward/Downward balancing energy provided by the BRP at time t (MW)
P_t^{DR}	Consumption of the DR resources at time t (MW)
λ_t^{SI}	Imbalance price at time t (€/MWh)
λ_t^{DR}	Energy price sent to DR resources at time t (€/MWh)
$s_{r^{+/-},t}$	Activated upward (+)/downward (-) regulation energy of bid r^+/r^- at time t (MW)
$p_{b,t}^{DR}$	Activated consumption of the DR resources for energy block b at time t (MW)

I. INTRODUCTION

In the quest towards a decarbonized energy supply, renewable energy resources (RESs) have experienced significant growth. However, their intermittent nature necessitates scheduling adequate flexible resources, including those on the demand side [1]. Demand response (DR) resources can be categorized into two groups based on their control interface and commitment: Explicit DR (EDR) resources [2], such as industrial loads, which are activated through direct control signals and have a contractual obligation to adjust their setpoints accordingly; and Implicit DR (IDR) resources, like small-scale residential loads, which voluntarily modify their consumption in response to market prices, taking into account their objectives and constraints without any commitment [3]. Mass mobilization and coordination of small-scale price-responsive loads through an aggregating entity can provide significant flexibility in the electricity system and promote system reliability [4]. For instance, their flexibility can be valorized in balancing markets to provide balancing energy to the network while reducing the energy bills of the participating DR resources [5]. However, the effective integration of IDR through price-based coordination remains a challenging task because the response of the IDR resources can only be measured ex-post after the clearing price of the market has been communicated to them. This coordination sequence can result

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in system volatility as the size of the IDR resources grows, making it necessary for the aggregating entity to develop behavioral models for the IDR [6].

Various methods have been explored in the literature for modeling demand flexibility. The authors in [7] employed a scenario-based approach to assess demand-side capacity participation in the reserve market. Similarly, the research in [8] explored the effects of strategic aggregator participation by leveraging demand response providers in the day-ahead market using a scenario-based chance-constrained model. These approaches require substantial computing power for generating scenarios to solve the resulting stochastic problem, which limits their use in time-sensitive applications. To combat this problem, data-driven models for price-demand elasticity have been proposed in the literature. To this end, in [9], the authors propose using Inverse Optimization (IO) to forecast the aggregate price-response behavior of a cluster of price-responsive loads by recasting their flexibility as market bids characterized by a set of energy blocks and corresponding utility functions. In [10], the authors extend the previous study to map the price response of a pool of electric vehicles in the form of a bid/offer curve. However, these studies only focused on the forecasting task and did not investigate the market participation of the IDR.

In order to bridge the gap between the forecasting task and the decision-making task, the authors in [11] propose a modified deep learning and reinforcement learning method to calculate the best incentive rates for DR at each hour to maximize the profit of the energy service provider. Similarly, the study in [12] proposes an integrated forecast and decision-making tool for DR in residential distribution networks. While these methods can effectively capture the demand response behavior, they necessitate the complete replacement of the decision-making optimization problem, which restricts their application and integration into existing power system studies.

Aiming to develop interpretable DR models, another line of research has emerged, focusing on DR behavior estimation using IO. In [13], the authors propose a data-driven approach for predicting price-responsive DR behaviors, incorporating prior model knowledge and using a gradient descent method to determine the best-fitting model parameters based on the historical price and response data. Similarly, in reference [14], DR behavior prediction is transformed into a quadratically constrained quadratic program and solved through successive linear programming. However, both studies primarily concentrate on modeling DR behavior without addressing its integration into market decision-making processes.

This paper builds upon the work in [9] and [14] to propose a novel data-driven IO framework that uses the past price-consumption data to infer the price-response behavior of the IDRs in the form of a flexibility curve characterizing IDR consumption bounds and corresponding willingness-to-pay. The model is then integrated into a bi-level Stackelberg market framework inspired by the Belgian single imbalance market [15] in which an aggregating entity called Balancing Responsible Party (BRP) uses the inferred flexibility curve to optimize its out-of-balance position and participates in the imbalance market. The proposed method can fill the information gap between the forecasting and decision-making tasks in [9]–[10], enabling the BRP to optimize the price signal that needs to be sent to IDR to elicit the desired response. Furthermore, unlike [11]–[12], our proposed model does not need to replace the optimization problem entirely. Instead, it can be integrated into the decision model as a linear lower-level problem.

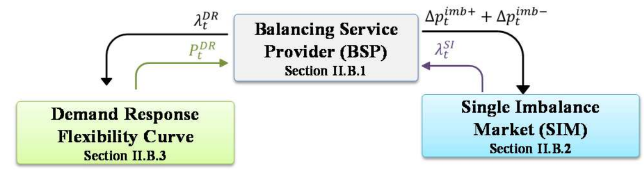

Figure 1. Interactions between the upper level and the lower-level problems

The rest of the paper is organized as follows: Section II provides an overview of the Belgian single imbalance market and presents the mathematical formulation of BRP's bi-level optimization problem. Section III describes the methodology for obtaining the flexibility characteristics of the price-responsive loads. The results and the investigated case study are presented in section IV. Finally, section V concludes the paper.

II. Model Description

This section describes the fundamentals of the balancing market and the bi-level structure that represents the interactions between the BRP, the balancing market, and the IDRs (Fig.1).

A. Balancing Markets

With the liberalization of the European electricity sector, the responsibility for maintaining equilibrium between electricity production and consumption, ensuring power system stability, now lies with market participants known as Balance Responsible Parties (BRPs). To facilitate the pursuit of this objective, the European market structure is divided into distinct energy-only and operating reserve services, which are traded consecutively through autonomous auctions. In this framework, BRPs are tasked with continually balancing their individual load and generation. The real-time residual imbalance at the system level is then rectified via a balancing mechanism, wherein the system operator utilizes reserve capacities provided by certain BRPs through the reserve capacity market. The expenses associated with the real-time activation of reserves are offset by imposing a fee on each imbalanced BRP. These charges, calculated (averaged) on a quarter-hour basis, are applied as soon as an imbalance arises. This mechanism is referred to as imbalance settlement. The European regulatory authorities have established guidelines for penalizing such imbalances using a single pricing settlement. This paper, therefore, examines this single-price imbalance settlement model, where all imbalance positions are settled at a uniform price [16]. This system rewards BRPs that contribute to rectifying system imbalances while penalizing those exacerbating the imbalance situation. Generally, the single imbalance price λ_t^{SI} depends on the actual volume of reserves activated by the system operator. In instances of a generation deficit within the grid ($\widehat{SI}_t < 0$), the system operator must activate upward reserves, the cost of which is characterized as the marginal incremental price (MIP). The BRPs accountable for this deficit are required to pay the MIP (typically greater than the day-ahead market price and thus less economical), while actors possessing excess generation receive this (highly attractive) MIP. Conversely, when a generation surplus exists ($\widehat{SI}_t > 0$) at the system level, the subsequent activation of downward reserves yields the marginal decremental price (MDP). BRPs with a generation surplus receive this MDP (usually lower and therefore less lucrative than the day-ahead energy price) for their surplus, whereas BRPs experiencing a generation deficit pay this (appealing) minimal MDP fee for their corresponding negative imbalance, as they aid in restoring the system balance.

B. Mathematical Formulation

The envisioned bi-level participation framework consists of three components: the upper level, hereafter referred to as the BRP problem, formulates the profit maximization of the BRP; the first lower-level problem, hereafter called the SIM problem, emulates the quarter-hourly clearing of the single imbalance market; and, the second lower-level problem, called the FC problem, represents the flexibility curve of the IDRs.

1) Balancing Service Provider (BRP)

$$\max_{\zeta_t} \sum_t \lambda_t^{SI}\left(\Delta p_t^{imb+} - \Delta p_t^{imb-}\right) + \lambda_t^{DR}\left(P_t^{DA} + \Delta p_t^{imb-} - \Delta p_t^{imb+}\right) - \lambda_t^{DA} P_t^{DA} \Delta t \quad \text{(BRP.1)}$$

$$\zeta_t := \left\{\Delta p_t^{imb+}, \Delta p_t^{imb-}, \lambda_t^{DR}, p_{b,t}^{DR}\right\}$$

$$\sum_b p_{b,t}^{DR} = P_t^{DA} + \Delta p_t^{imb-} - \Delta p_t^{imb+} \qquad \forall t \in \mathcal{T} \quad \text{(BRP.2)}$$

$$0 \le \Delta p_t^{imb-} \le \left(P_t^{DR} - P_t^{DA}\right) U_t^- \qquad \forall t \in \mathcal{T} \quad \text{(BRP.3)}$$

$$0 \le \Delta p_t^{imb+} \le \left(P_t^{DA} - P_t^{DR}\right) U_t^+ \qquad \forall t \in \mathcal{T} \quad \text{(BRP.4)}$$

$$0 \le \lambda_t^{DR} \le \overline{\lambda_t^{DR}} \qquad \forall t \in \mathcal{T} \quad \text{(BRP.5)}$$

In the problem above, the first term of BRP's objective function (BRP.1) tries to maximize its profit in the single imbalance market by increasing its consumption and providing downward balancing energy (Δp_t^{imb-}), or decreasing its consumption and providing upward balancing energy (Δp_t^{imb+}), with respect to its baseline, cleared day-ahead consumption setpoint (P_t^{DA}). In this term, the single imbalance price (λ_t^{SI}) is the dual variable of the (SIM) lower-level problem (section II.B.2). Here, it is assumed that the only source of flexibility available to the BRP is IDR resources whose behavior is captured through the FC problem (section II.B.3). Equation (BRP.2) defines how the BRP can provide balancing energy by inducing a change in the DR energy consumption (by sending λ_t^{DR}). The second term of the objective function defines the transaction between BRP and the IDR resources. Equations (BRP.2)–(BRP.4) define the bounds of downward and upward balancing energy and make sure that, at each time step, only one of them is activated ($U_t^- = 1$ only if $\widehat{SI}_t > 0$, and $U_t^+ = 1$ only if $\widehat{SI}_t < 0$). Equation (BRP.5) enforces the upper bound of the price sent to DR.

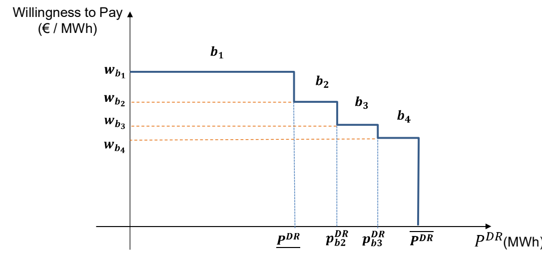

Figure 2. Flexibility curve of price-responsive loads at time t

Lastly, the third term of the objective function is the amount of money the BRP has already paid for obtaining its baseline P_t^{DA}. This term ensures that the BRP participates in the single imbalance market only when its profits outweigh the costs of deviating from its day-ahead commitment.

2) Single Imbalance Market (SIM)

$$\min_{s_{r^+,t}^+, s_{r^-,t}^-} \sum_{r^+} \Lambda_{r^+,t}\, s_{r^+,t} - \sum_{r^-} \Lambda_{r^-,t}\, s_{r^-,t} \quad \text{(SIM.1)}$$

$$\sum_{r^-} s_{r^-,t} - \sum_{r^+} s_{r^+,t} + \Delta p_t^{imb-} - \Delta p_t^{imb+} - \widehat{SI}_t = 0 : \lambda_t^{SI} \qquad \forall t \in \mathcal{T} \quad \text{(SIM.2)}$$

$$0 \le s_{r^+,t} \le \overline{S}_{r^+,t} \qquad \forall t \in \mathcal{T}, \forall r^+ \in \mathcal{R}^+ \quad \text{(SIM.3)}$$

$$0 \le s_{r^-,t} \le \overline{S}_{r^-,t} \qquad \forall t \in \mathcal{T}, \forall r^- \in \mathcal{R}^- \quad \text{(SIM.4)}$$

This subproblem emulates the market clearing problem of the TSO [15], which aims to minimize the cost of reserve activation (SIM.1). The impact of the BRP's imbalance position on the reserve activation can be seen in (SIM.2). Moreover, the maximum amount of energy for upward and downward bids are observed in (SIM.3) and (SIM.4), respectively.

3) IDR Flexibility Curve (FC)

$$\max_{p_{b,t}^{DR}} \sum_b p_{b,t}^{DR}\left(w_{b,t} - \lambda_t^{DR}\right)\Delta t \quad \text{(FC.1)}$$

$$\underline{P^{DR}}_t \le \sum_b p_{b,t}^{DR} \le \overline{P^{DR}}_t \qquad \forall t \in \mathcal{T} \quad \text{(FC.2)}$$

$$0 \le p_{b,t}^{DR} \le E_{b,t} \qquad \forall t \in \mathcal{T}, \forall b \in \mathcal{B} \quad \text{(FC.3)}$$

This subproblem represents the price response of the IDR resources. This price response is captured through three main parameters i.e. $w_{b,t}$, $\overline{P^{DR}}_t$, and $\underline{P^{DR}}_t$ (Fig. 2), which are all obtained through IO (Section III). The objective of this problem (FC.1) is to maximize the consumption of the DR resources based on the matching between the energy price signal communicated by the BRP (λ_t^{DR}) and the estimated willingness-to-pay ($w_{b,t}$). In (FC.2), the constants $\overline{P^{DR}}_t$, and $\underline{P^{DR}}_t$ define the maximum and minimum DR consumption, respectively, and $p_{b,t}^{DR}$ defines the consumption block activated by the price signal (λ_t^{DR}). The maximum amount of energy

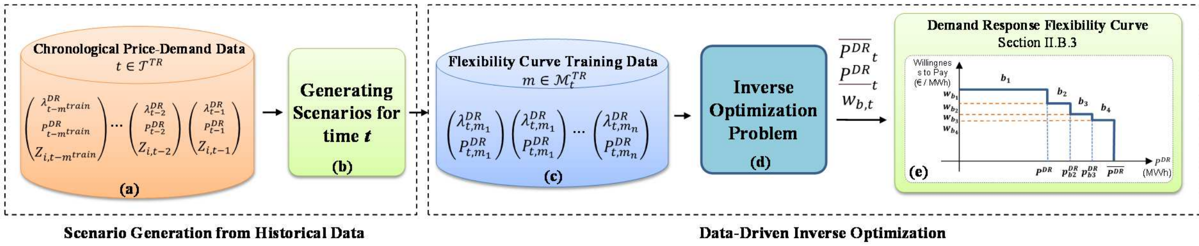

Figure 3. The overall schematic of data flow for obtaining the values of IDR flexibility curve

activated in each block ($E_{b,t}$) is observed in (FC.3). It should be noted that the parameter $E_{b,t}$ is calculated based on the estimated consumption bounds and a pre-defined number of energy blocks in the flexibility curve.

$$E_{b,t} = \begin{cases} \underline{P^{DR}}_t & if\ b = b_1 \\ \dfrac{\overline{P^{DR}}_t - \underline{P^{DR}}_t}{|\mathcal{B}|} & if\ b > b_1 \end{cases} \quad \forall t \in \mathcal{T} \qquad \text{(FC.4)}$$

III. Data-Driven Inverse Optimization

This section delves into the details of how the main parameters of the (FC) problem are inferred from the anticipated price-demand data pair (Fig. 3). In the first step, the historical data of price-demand (Fig. 3(a)) are used to generate random price-demand pairs (Fig. 3(b)-(c)). Next, the generated demand scenarios $P_{t,m}^{DR,Scn}$ enter the objective of the upper level (IO.1), and the corresponding price scenarios $\lambda_{t,m}^{DR}$ enter the objective function of the flexibility curve at the lower level (IO.4) as inputs. The goal of the IO problem is to determine the main parameters of the flexibility curve (i.e. $w_{b,t}, \overline{P^{DR}}_t, \underline{P^{DR}}_t$) such that the distance between $P_{t,m}^{DR,Scn}$ and estimated demand by the FC ($P_{t,m}^{DR}$) corresponding to $\lambda_{t,m}^{DR,Scn}$ (IO.4) is minimum (IO.1), taking into account all the scenarios of the training set ($s \in \mathcal{M}_t^{TR}$).

Equation (IO.2) forces the estimated willingness-to-pay values to decrease monotonically. Similarly, (IO.3) ensures that the willingness-to-pay of the first energy block corresponding to the minimum DR demand gets activated regardless of the price signal. In the lower-level problem, which corresponds to the FC problem, the objective is to maximize the utilization of the DR resources with respect to the transmitted energy price (IO.4). Equation (IO.5) defines the aggregate DR demand, and its bounds are observed in (IO.6). The maximum amount of energy activated in each block ($E_{b,t}$) and its relationship to the main FC parameters are detailed in (IO.7) and (IO.8). The resulting IO cannot be directly solved in a tractable manner and necessitates the implementation of various techniques (e.g., linearization of the absolute value in the objective function and reformulation of the lower level). For further details on the IO problem, readers are encouraged to refer to [9].

$$\min_{\theta} \sum_{m \in \mathcal{M}_t^{TR}} \omega_m \left| P_{t,m}^{DR} - P_{t,m}^{DR,Scn} \right| \qquad \text{(IO.1)}$$

$$\theta := \{P_{t,m}^{DR}, w_{b,t}\}$$

$$w_{b,t} \geq w_{b+1,t} \quad \forall t \in \mathcal{T}^{TR}, \forall b \in \mathcal{B} \qquad \text{(IO.2)}$$

$$w_{b_1,t} \geq w_{b_2,t} + K \quad \forall t \in \mathcal{T}^{TR}, \forall b \in \mathcal{B} \qquad \text{(IO.3)}$$

$$\{P_{t,m}^{DR}, w_{b,t}\} \in \underset{\vartheta}{\operatorname{argmax}} \sum_{b} p_{b,t,m}^{DR}\left(w_{b,t} - \lambda_{t,m}^{DR,Scn}\right) \qquad \text{(IO.4)}$$

$$\vartheta := \left\{p_{b,t,m}^{DR}, \overline{P^{DR}}_t, \underline{P^{DR}}_t\right\}$$

$$P_{t,m}^{DR} = \sum_{b} p_{b,t,m}^{DR} \quad \forall t \in \mathcal{T}^{TR}, \forall b \in \mathcal{B}, \forall m \in \mathcal{M} \qquad \text{(IO.5)}$$

$$\underline{P^{DR}}_t \leq \sum_{b} p_{b,t,m}^{DR} \leq \overline{P^{DR}}_t \quad \forall t \in \mathcal{T}^{TR}, \forall b \in \mathcal{B}, \forall m \in \mathcal{M} \qquad \text{(IO.6)}$$

$$0 \leq p_{b,t,m}^{DR} \leq E_{b,t} \quad \forall t \in \mathcal{T}^{TR}, \forall b \in \mathcal{B}, \forall m \in \mathcal{M} \qquad \text{(IO.7)}$$

$$E_{b,t} = \begin{cases} \underline{P^{DR}}_t & if\ b = b_1 \\ \dfrac{\overline{P^{DR}}_t - \underline{P^{DR}}_t}{|\mathcal{B}|} & if\ b > b_1 \end{cases} \quad \forall t \in \mathcal{T}^{TR} \qquad \text{(IO.8)}$$

IV. Case Study

In this section, we analyze the performance of the method developed for inferring the parameters of the flexibility curve and its implementation into the Single Imbalance Market.

A. Input Data and Assumptions

The historical price-demand data for DR (Fig .3 (a)) are obtained by solving the cost minimization problem of EV smart charging [17] for the span of 90 days before the test date (January 29th, 2020) based on data from the Caltech University EV database [18] and day-head energy prices of Belgium [19]. In the next step, the historical EV charging data were used to generate 500 random samples from the joint distribution of the EV consumption and the corresponding day-ahead energy prices (Fig. 3(b)). In the third step, the generated data pairs (Fig. 3(c)) were used to infer the parameters of the flexibility curve (Fig. 3(d)). Once the flexibility curve of the DR gets calculated, it can be incorporated into the decision-making process (Fig. 1) as the lower-level problem. The flexibility curve obtained for the test time slot (first quarter of hour 6 on the test day) as well as the maximum amount of upward and downward flexibility available to the BRP, based on its DA position, is depicted in Fig. 4. The merit order data for reserve providers for the test time slot are presented in Table I [20].

TABLE I. The Reserve Bids on the Test Time Slot

	$r_1^{+/-}$	$r_2^{+/-}$	$r_3^{+/-}$	$r_4^{+/-}$	$r_5^{+/-}$
Λ_{r^+} (€/MWh)	55.85	58.23	58.33	58.43	4500
Λ_{r^-} (€/MWh)	5.63	-110.2	-168.3	-278.9	-279
$s_{r^{+/-}}$(MW)	100	100	100	300	300

B. Results

The performance of the proposed method has been assessed in different cases to examine how the new information provided by the flexibility curve can help the BRP make more informed decisions about participating in the Single Imbalance Market by deviating from its DA setpoint. Five cases have been defined to represent different system-level imbalance states (Table II): C1–C3 for generation surplus conditions and C4–C5 for generation deficit conditions. In Table II, the $\widehat{SI}_t$ column displays the system imbalance for each case, while the λ_t^{SI} column indicates the single imbalance price taking into account the deployment of IDR resources. The λ_t^{DR} column represents the price signals sent by the BRP to IDR to attain the optimal out-of-balance position (Δp_t^{imb+} or Δp_t^{imb-}), maximizing profit in the single imbalance market. The table also contains the profits projected by the proposed method. The SIM column reveals the expected profit from providing the balancing energy. To achieve this profit, the BRP must alter the price sent to the IDRs, consequently compromising the potential for selling energy at the DA volume and prices. The "DR Net" column accounts for the compromised retail profit in each case, illustrating the difference between the amount charged to the DR and the cost of procuring the DA working point:

$$DR\ Net = \lambda_t^{DR}\left(P_t^{DA} - \Delta p_t^{imb+} + \Delta p_t^{imb-}\right) - \lambda_t^{DA} P_t^{DA}$$

The "Net" column shows that by compromising the prospect of selling energy at the DA prices, the BRP was able to make a substantial profit from participation in the balancing market. Furthermore, the results show that the flexibility curve allows the BRP to participate in the balancing market only when its costs are covered by λ_t^{SI}. For example, in the case C1, the BRP fully deploys downward balancing flexibility and gains 919.84 €. Case C2 illustrates the optimal decision for the BRP when λ_t^{SI} drops to 20 € (by altering the reserve bids presented for the base case in Table I). At this price, it is no longer profitable for the BRP to fully deploy its downward balancing flexibility, as the cost of the required subsidy to achieve full deployment exceeds the potential earnings from the balancing market. Case C3 shows that if λ_t^{SI} falls even further, it becomes more profitable for the BRP to maintain its DA energy levels by sending (λ_t^{SI}=λ_t^{DA}) and not participate in the balancing market.

On the other side of the system imbalance spectrum, cases C4 and C5 demonstrate how the BRP can contribute to the upward balancing service by reducing its consumption. The DR Net column reveals that although the BRP sells energy at higher prices during those time slots, the reduced consumption leads to lower retail revenues, which are offset by remuneration in the balancing market.

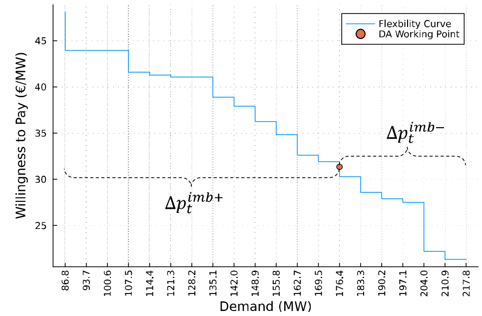

Figure 4. Generated price scenarios for the test time slot

To verify the performance of sthe proposed method, an XGboost forecasting module has been trained using the historical data (Fig. 3 (a)). It was then used to calculate the values in the ex-post column. To that end, the λ_t^{DR} price calculated by BRP is fed into the XGBoost forecasting module to predict the actual demand response pertaining to the transmitted price. Based on this new forecast value, the actual values of upward or downward balancing are determined, and profits are adjusted according to the actual responses. However, as can be observed in the ex-post columns, the flexibility curve slightly overestimated the actual deployment of DR, resulting in reduced actual profit for the BRP. Although the flexibility curve tends to overestimate the amount of response in the cases presented above, there are situations where it underestimates the response. This underestimation could lead to financial penalties if the BRP's portfolio is large enough to tip the system imbalance in the opposite direction.

V. Conclusion

This paper has proposed a novel data-driven approach to model DR resources through their aggregate forecasts using IO. The proposed method utilizes historical price and consumption data to deduce IDR price-response behavior via a flexibility curve, which can then be used to optimize a BRP's strategic imbalance positions by managing DR resources through suitable price signals. The accuracy of the estimated flexibility provided by the proposed algorithm was evaluated by comparing its outcomes with those obtained from the XGboost method. The comparison results demonstrated that the model could effectively capture IDR behavior and generate profit. The insights obtained from this study can provide valuable information for BRPs and system operators to understand the price-response of DR resources better and facilitate their economic integration into electricity markets.

TABLE II. Results of BRP participation in balancing market under different scenarios

Case	$\widehat{SI}_t$	λ_t^{SI}	λ_t^{DR}	Proposed Method					Ex-Post Verification				
				Δp_t^{imb+}	Δp_t^{imb-}	Profit			Δp_t^{imb+}	Δp_t^{imb-}	Profit		
						SIM	DR Net	Net			SIM	DR Net	Net
C1	150	-110.2	21.32	0	41.42	1141.2	-221.42	919.84	0	41.08	1131.9	-223.24	908
C2	150	-20	27.55	0	27.61	138	23.1	161.19	0	23.21	116	-7.2	108
C3	150	2	31.35	0	0	-	0	-	0	0	-	0	-
C4	-150	55.85	49.63	89.75	0	1253.2	-307.45	945.7	89.75	0	1253.2	-307.45	945.76
C5	-84	55.85	47.44	84	0	1172.8	-286.68	886	83.76	0	1169.6	-283.94	885.68

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