Assessing the Impact of Grid Constraints on Aggregated Flexibility for Energy Market Participation

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Abstract— **The integration of renewable energy sources and distributed generation highlights the need to leverage consumer flexibility for grid management. An effective way to incentivize it is to foster their participation in the balancing and flexibility markets, where aggregated consumers' commit to change their consumption in real-time according to their bids before real-time. Therefore, it is relevant to prevent congestions and account for grid losses when forecasting the available flexibility to form the market bid. This paper evaluates the impact of grid conditions on aggregated flexibility from an energy community, analyzing how incentive-driven scenarios influence flexibility under constrained and unconstrained grid conditions. Using grid simulations and data-driven profiles of consumer flexibility, the analysis explores the effects of technical constraints such as line capacity, voltage regulation, and transformer loading. Results highlight how grid conditions can reduce or, in some cases, enhance flexibility by improving voltage profiles, managing reactive power, and redistributing loads. The findings quantify realistic flexibility considering grid constraints and emphasize the role of incentives in extracting said flexibility effectively. This paper aims to guide market participants in optimizing demand response strategies for a resilient power system.**

Index Terms-- **Aggregated Flexibility, Distributed Energy Resources, Grid Constraints, Incentive-based Demand Response, Energy Elasticity.**

I. Introduction

The increasing integration of renewable energy sources (RES) and distributed energy resources (DER) into modern power systems has highlighted the critical role of consumer flexibility in grid management and energy market participation. As grids evolve toward greater decentralization, the ability of consumers to adjust their energy consumption or production in response to price signals, operational needs, or incentives becomes a valuable tool for improving power system security, reducing operational costs, and facilitating market participation [1]. Aggregated consumer flexibility not only supports real-time grid balancing but also enables participation in ancillary services markets, making it a key enabler for sustainable and efficient energy systems [2].

Research on demand-side flexibility has advanced significantly in recent years, driven by the need to manage the variability and uncertainty introduced by RES. Existing studies have focused on modeling consumer flexibility, estimating price elasticity, and exploring the role of flexibility in power system security and market operations [3]. Data-driven techniques, including machine learning and statistical models, have been widely applied to predict consumer responsiveness and develop detailed flexibility profiles [4]. Notably, flexibility's role in enabling active participation in energy markets, particularly for ancillary services such as balancing and reserves, has gained prominence in both academic and industrial research [5].

Despite these advancements, several gaps remain. Many studies assume idealized conditions without considering the practical constraints imposed by the grid, such as voltage limits, line capacities, and localized losses. This limits the applicability of findings to real-world scenarios [6]. Second, most research focuses on either consumer behavior or grid-level impacts, with limited integration of the two domains. The interaction between consumer-driven flexibility and grid constraints, especially under varying incentive scenarios, requires better understanding [7]. Third, while elasticity is commonly used to measure consumer responsiveness, the implications of high and low elasticity values on aggregated flexibility in constrained grids remain underexplored [8]. Finally, there is a lack of systematic approaches to quantify the difference between theoretical and practical flexibility, particularly in the context of market participation [9].

Currently, many retailers lack precise knowledge of their customers' flexibility and their response to demand response (DR) signals. Residential electricity consumers are often reluctant to participate in volatile pool markets, and even when exposed to time-varying pricing, short-term electricity consumption remains nearly inelastic [10], [11]. Furthermore, DR programs relying on direct load control (DLC) provide some control over residential loads but face limitations such as operating within restricted time windows and requiring substantial customer engagement, hardware installations, or recurring payments [12]. Even with DLC, peak system demand may occur outside available DR periods, highlighting the need for dynamic, incentive-driven tariffs that can aggregate consumer flexibility while minimizing inconveniences.

Addressing these gaps involves several challenges. One key challenge is accurately estimating flexibility at the individual consumer level while accounting for behavioral variability and external factors such as weather and economic conditions [13]. Another challenge lies in integrating these detailed flexibility profiles into grid simulations that incorporate real-world

979-8-3503-8174-0/24/$31.00

constraints. Grid conditions, such as transformer capacities, line limits, and voltage regulation, add complexity to the evaluation of flexibility's impact on power flows and losses [14]. Additionally, the variability in consumer responsiveness under different incentive scenarios introduces uncertainty into the assessment of aggregated flexibility. Accurately forecasting flexibility potential and submitting realistic bids in energy markets remains a critical challenge for retailers and aggregators, as consumer response to DR signals is highly variable [15]. Traditional models assume fixed elasticity, leading to inaccurate predictions and suboptimal market participation.

This work addresses these challenges by estimating and analyzing aggregated flexibility within a low-voltage (LV) grid comprising residential and industrial loads, as well as renewable generation sources. Flexibility is modeled based on consumer responsiveness to incentives, characterized through elasticity profiles derived from data-driven analyses [16]. Scenarios are designed to capture flexibility under different conditions, reflecting real-world variability in consumer behavior. The flexibility profiles are integrated into grid simulations to assess the impacts of grid constraints on the available flexibility. This step is crucial for quantifying the practical limits of flexibility when considering technical constraints. By analyzing the percentage difference between unconstrained and constrained flexibility scenarios, the study highlights the interplay between technical limitations and consumer behavior. Additionally, the findings emphasize the potential for grid conditions to occasionally enhance flexibility through optimized power flows, challenging the assumption that constraints always reduce available flexibility [17]. This study addresses this gap by dynamically estimating hourly elasticity profiles, enabling retailers to assess available flexibility with greater precision, leading to other decisions on optimize bid placement, and minimize financial penalties. By incorporating consumer-specific flexibility potential, this approach enhances bid security and network reliability while mitigating financial risks. Unlike conventional methods that assume uniform demand adjustments, this work quantifies flexibility under varying incentives and evaluates the impact of grid constraints, ensuring that submitted bids align with actual flexibility availability. This framework improves DR market integration by reducing over- and under-commitments, advancing realistic flexibility forecasting for market participation.

II. Methodology for Estimating Aggregated Flexibility

This methodology outlines the steps for estimating the aggregated flexibility available for participation in energy markets, accounting for grid losses and consumer behavior. The process integrates flexibility estimation, elasticity calculations, and grid simulations. The system consists of a LV grid with residential and industrial loads (as shown in Figure 1), as well as RES (PVs and wind). Below is an overview of the process and how the flexibility is calculated and incorporated into grid operations.

A. Data Collection and Grid Setup

The initial generation and consumption information comes from a substation of the Portuguese network, providing the basis for scaling and implementing the LV grid with RES. Specifically, data on solar PV and wind generation are scaled to model two PV systems (one on bus B and one on bus C) and one wind generator (on bus DI). The power system comprises a high-voltage transmission network operating at 110 kV, with Bus 1 serving as the main voltage reference point. Power is stepped down to 20 kV at Bus 300 via a transformer; this bus includes a battery energy storage system that accounts for system losses by dynamically absorbing excess power, ensuring a realistic estimation of grid losses while maintaining network security. Another transformer connects Bus 300 to Bus 310, reducing the voltage to 0.4 kV for low-voltage distribution.

The low-voltage distribution network centers around Bus 310 and includes several key buses: Bus 311 ('A'): Supplies residential loads; Bus 312 ('B'): Hosts high-consuming residential loads and a PV generator – 0.5MW of installed capacity; Bus 313 ('C'): Supplies residential loads and includes another PV generator of 2MW installed capacity; Bus 314 ('DI'): Serves an industrial load and incorporates a wind generator of 5MW of installed capacity; Bus 324 ('D'): Supplies additional residential loads. The grid integrates RES at Buses 312 and 313 (PV systems) and Bus 314 (wind generator) with residential and industrial loads. This setup allows for distributed generation to supplement the main power supply, enhancing efficiency and sustainability within the network. The combination of centralized generation, distributed RES, and energy storage ensures reliable power delivery to both residential and industrial consumers while facilitating the analysis of grid losses through the battery (1 MW) at Bus 300.

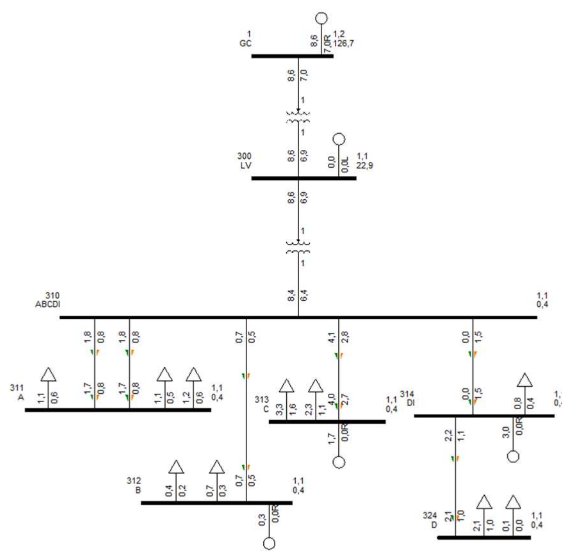

Figure 1 Low-Voltage 400V grid

B. Power Flow Setup

The power flow setup involves conducting two sequential simulations to assess the impact of consumer flexibility on grid losses and system security. In the first simulation, Bus 1 (the grid connection point) is set as the swing bus, keep the battery at Bus 300 out of service, and apply a specific load scenario (e.g., maximum flexibility) to all residential and industrial consumers. This establishes baseline power flow results and records the total power supplied by the grid. In the second simulation, change Bus 1 to a PV bus with its active power generation fixed at the value obtained from the first run, and set Bus 300 as the new swing bus with the battery now in service. By keeping the load scenario consistent, the battery at Bus 300 automatically adjusts its power output to balance the system, effectively absorbing the grid losses. This approach allows to quantify how different flexibility levels affect grid losses and system performance. Initial Power Flow - The grid-connected (GC) bus is set as the slack bus for the initial power flow calculations, which determines the baseline values for power flows and losses. Slack Bus Transition - After obtaining the initial results, the slack bus is changed to bus LV to estimate the grid losses more precisely. This approach allows the comparison of different scenarios of flexibility and their impact on the grid's performance.

The implementation process includes two main power flow runs to assess the system's behavior under different conditions. In the first power flow run (Base Case), Bus 1 (GC) is designated as the swing bus, while Bus 300 (LV) is a PQ bus with the battery out of service. The loads are set to the desired flexibility scenario (e.g., maximum flex), and a power flow is performed to determine baseline results, including total power supplied by the grid at Bus 1. In the second power flow run (Battery Absorbing Losses), Bus 1 (GC) is changed to a PV bus, with its active power generation (PG) and voltage magnitude set to the values obtained from the base case, or to desired levels. Meanwhile, Bus 300 (LV) becomes the swing bus with the battery generator in service; here, power flow simulation adjusts the battery's PG to balance the system. The loads remain at the same flexibility scenario, and the battery's final PG value at Bus 300 represents the absorbed grid losses. By fixing the generation at Bus 1 to the value obtained in Run 1, we ensure that any difference in power balance must be accounted for by the battery at Bus 300. The battery's power output in Run 2 effectively captures the grid losses since it compensates for the difference between fixed generation and actual load demand plus losses.

III. Flexibility Estimation Process

The flexibility estimation process involves several key steps, starting with data collection from the Portuguese network and prosumer sources (meter, wind, and PV). This data is scaled and adapted to reflect a realistic LV grid with RES. A 24-hour flexibility profile is then estimated for each consumer, capturing their potential response to price incentives. Three scenarios are analyzed: high incentive, where consumers with high elasticity reduce consumption; low incentive, where they increase consumption; and a baseline scenario with no incentives. Finally, the flexibility data is integrated into power flow simulation simulations to evaluate grid behavior, focusing on grid losses, security, and aggregated flexibility at the connection point.

A. *Flexibility Model*

The developed model utilizes a causality-based inference algorithm [18] to analyze each consumer's 24-hour energy consumption profile, incorporating maximum and minimum flexibility bounds derived from using machine learning models, such as Random Forest/Kernel regression. The method estimates expected hourly consumption and generates confidence intervals to define potential flexibility ranges. A causal inference framework [19], based on the parametric g-formula and leveraging time-varying confounders (e.g., temperature, time, and calendar features), estimates the impact of DR pricing on consumption using the Robin g-method. This model calculates the causal relationship between price and consumption, while controlling for confounders. Nonparametric regression using a Gaussian kernel function estimates the conditional expectation of consumption, and bootstrapping addresses uncertainty due to the uneven frequency of DR pricing events. The model outputs hourly flexibility estimates for each consumer, providing upper and lower consumption bounds to quantify elasticity and support demand response strategies.

B. *Elasticity estimation model*

Elasticity estimation model is used to calculate the price elasticity of demand (PED) for each consumer based on their responsiveness to price signals. This step involves calculating how consumption changes relative to price variations across the 24-hour profile for each consumer. The responsiveness is critical for determining the actual flexibility consumers can offer in energy markets. It is calculated using the following relationship:

$$PED = \frac{\%\text{ change in consumption}}{\%\text{ change in price}}$$

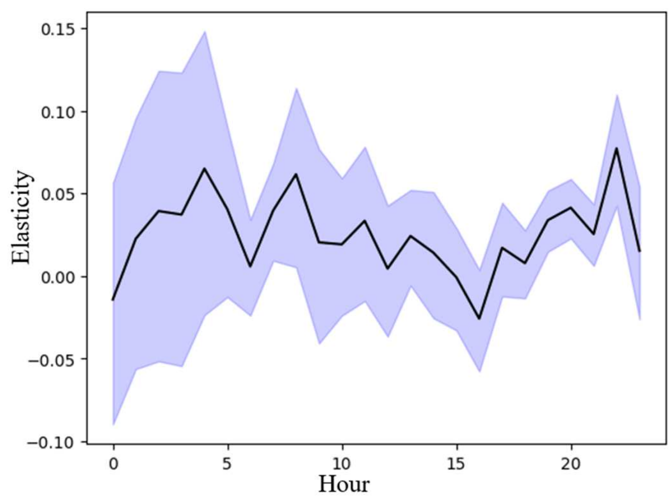

Figure 2 Consumer-A elasticity profile for high incentive

High price elasticity and low-price elasticity shows how much the consumption decreases or increases when prices rise. If consumers are responsive to price increases, they will reduce their energy, and vice versa. But this is not always true, as consumers are more prone to make changes based on their comfort levels and the effect of price changes vary from one consumer to another (example of some consumers maybe inelastic to price changes as they prefer their comfort compared to financial gains). A positive elasticity indicates that consumption increases when prices decrease (for low prices) or decreases when prices increase (for high prices). This is the ideal expected response. A negative elasticity indicates that consumption moves in the opposite direction, which means that consumers are not very responsive to price changes, or that external factors are influencing their behavior. The resulting elasticity values are then applied to generate three distinct flexibility scenarios; incentive to reduce (high incentive) -

consumers are highly responsive to price signals, adjusting their consumption significantly; incentive to increase (low incentive) - consumers exhibit minimal responsiveness; and no incentive - consumers do not respond to price signals at all.

The elasticity plots (figures 2 and 3) illustrate the elasticity profile of Consumer-A under two incentive conditions—high and low—over a 24-hour period. In Figure 2, we see Consumer-A's elasticity profile for high incentive conditions, such as during periods of elevated energy prices. The elasticity values are mostly positive, indicating that Consumer-A tends to reduce consumption in response to high prices, demonstrating a degree of flexibility aligned with market signals. The black line represents this positive elasticity trend, while the shaded purple area captures the variability or confidence interval, reflecting fluctuations in the consumer's responsiveness across different hours. This variability suggests that while Consumer-A generally reduces consumption when prices are high, their exact response can differ due to factors such as time of day or external conditions. In Figure 3, Consumer-A's elasticity profile is shown under low incentive conditions, such as during low-price periods. Here, the elasticity values are mostly negative, indicating that Consumer-A does not respond as expected to low prices. Instead of increasing consumption to take advantage of lower prices, Consumer-A appears to either reduce consumption or make minimal adjustments. The shaded area again shows the confidence interval, and it is relatively wide, indicating considerable variability and unpredictability in responsiveness under low incentive conditions. This suggests that low prices alone may not be enough to stimulate additional energy use from Consumer-A, either due to constraints or a lack of motivation to adjust consumption in this scenario. Overall, these charts imply that Consumer-A's flexibility is more consistent and reliable under high-price conditions, which could be useful information for grid operators and market participants seeking to mobilize demand-side flexibility.

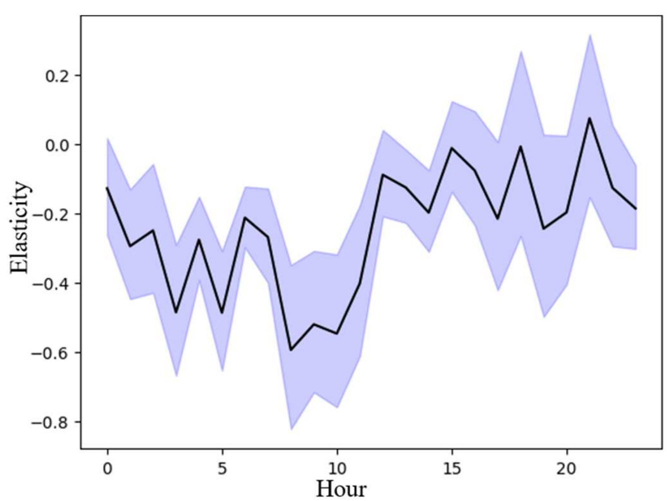

Figure 3 Consumer-A elasticity profile for low incentive

C. Scenario-Based Power Flow Simulation

The estimated flexibility and elasticity profiles for each consumer is used to simulate the grid's behavior under different flexibility scenarios. This is performed using PSSE (Power System Simulator for Engineering), a comprehensive tool for power flow analysis that enables detailed simulation of electrical networks. The objective of these scenario-based simulations is to assess how various levels of consumer flexibility impact grid performance, particularly focusing on grid losses and stability, under different incentive conditions. By modeling the power flow under these scenarios, we can better understand the extent to which the aggregated flexibility of the energy community can support grid operations and participate effectively in energy markets. The battery on bus LV helps balance power by absorbing excess energy, contributing to loss management, and its impact on system losses is assessed across different scenarios.

1) Aggregated Flexibility and Grid Losses

For each scenario, two sets of power flow simulations are executed. In the first set, the GC bus is set as the slack bus. The slack bus is responsible for balancing power in the system and compensating for losses, making it essential for accurately assessing the overall grid behavior under different flexibility levels. Setting GC as the slack bus reflects standard grid operations where the main utility connection supports the load. After obtaining initial results, the LV bus is set as the slack bus for the second set of simulations. Shifting the slack bus to the LV bus provides a localized view of grid losses within the energy community and allows for a finer assessment of how flexibility at the low-voltage level impacts grid efficiency. This two-part setup ensures a comprehensive evaluation of losses and helps capture the impact of consumer flexibility on both the main grid and the local community network. The results from these power flows are then used to estimate the aggregated flexibility for the entire grid, accounting for the influence of grid losses and varying consumer responses. The power flow simulations conducted over 24 iterations, each representing a 30-minute interval, analyzed the impact of reconfiguring bus types and generator statuses on system performance. In the initial power flow run (Base Case), Bus 1 was set as the swing bus, supplying both active (P) and reactive (Q) power to balance the system, while the battery at Bus 300 was out of service. The results showed that Bus 1 adjusted its active power generation according to load demands, with PGen values varying and QGen ranging from approximately 1.15 to 2.41 MVAr. In the second power flow run, Bus 1 was reconfigured as a PV bus (Type 2) with a fixed active power output and specified voltage magnitude, and Bus 300 became the swing bus with the battery brought into service. The battery at Bus 300 effectively absorbed the system's active power losses by discharging (injecting small amounts of active power into the grid) and provided reactive power support by absorbing reactive power (negative Qgen values ranging from approximately -2.68 to -6.58 MVAr). This shift allowed Bus 1 to maintain its specified voltage while significantly increasing its reactive power output to support the new system configuration.

The notable increase in reactive power generation at Bus 1 after the reconfiguration aligns with the expected behavior of a PV bus tasked with voltage regulation under altered system conditions. The battery's operation at Bus 300 successfully reduced the active power burden on Bus 1 and contributed to voltage stability through reactive power absorption. The total system losses slightly increased after the bus type change, which is consistent with the redistribution of power flows and the additional reactive power adjustments required. The simulation results validate the strategy of utilizing the battery at Bus 300 to absorb system losses and support voltage regulation. Reconfiguring Bus 1 to a PV bus and Bus 300 to a swing bus with the battery in service effectively demonstrates the battery's role in enhancing system performance. This approach reduces the strain on primary generators, balances power flows, minimizes losses, and improves voltage profiles, showcasing the benefits of integrating battery energy storage systems into power grids.

D. *Results and discussion*

Table 1 Comparison of Aggregated Flexibility with and without Grid Conditions across Different Incentive Scenarios

	Aggregated Flexibility Without Grid Conditions (kW)			Aggregated Flexibility With Grid Conditions (kW)		
Time period	Incentive			Incentive		
	High	Low	No	High	Low	No
00:00:00	4.3997	3.4882	4.3050	4.4303	3.4882	4.3298
00:30:00	3.8701	2.9083	3.8170	3.8907	2.9013	3.8340
01:00:00	4.3564	3.3522	4.3570	4.3848	3.3493	4.3852
01:30:00	2.0506	1.7311	2.0480	2.0182	1.6936	2.0152
...	…	…	…	…	…	…
08:30:00	8.4652	4.2355	8.5110	4.8243	0.3556	4.8661
09:00:00	5.8854	1.8496	6.0220	1.8395	-2.0597	1.9804
09:30:00	6.1168	2.1281	6.2310	1.9091	-1.8322	2.0265
10:00:00	5.9183	3.5503	5.9880	1.6506	-0.7547	1.7219
10:30:00	4.9131	2.9779	4.9390	0.7774	-1.1799	0.8056
11:00:00	6.6484	4.7361	6.9450	2.5780	0.7459	2.8890
11:30:00	5.8183	3.3446	5.9560	0.9956	-1.3693	1.1371
12:00:00	4.1145	3.2440	4.2920	-0.7433	-1.6194	-0.5632
...	…	…	…	…	…	…
19:00:00	13.8567	12.2584	13.0820	13.7536	11.9180	12.8355
19:30:00	13.4541	12.2142	12.6590	13.9971	12.5595	13.0549
20:00:00	9.8845	9.0913	9.7270	10.2365	9.3800	10.0581
...	…	…	…	…	…	…
23:00:00	6.8416	5.1232	5.9600	7.0333	5.2277	6.0787
23:30:00	4.1170	2.9475	4.0250	4.1456	2.9416	4.0490

The simulation results for each scenario provide insights on how different levels of incentive-driven flexibility impact the grid's power flow, grid losses, and voltage stability. The high incentive scenario typically demonstrates the greatest reduction in realized flexibility, as consumer responsiveness is maximized, allowing for optimal load distribution and load shaping across the network. The low incentive scenario shows a more moderate reduction in realized flexibility, reflecting the impact of limited flexibility. Finally, the baseline scenario highlights the inherent grid losses and characteristics in the absence of incentives, serving as a control to measure the effectiveness of consumer flexibility under incentivized conditions.

Through these scenario-based power flow simulations, we assess the technical benefits of aggregated flexibility in supporting energy market participation. This analysis identifies the potential of responsive consumers to contribute to power system needs and loss reduction when flexibility is limited or absent. By quantifying the value of flexibility under different incentive conditions, this approach informs strategies for effectively leveraging demand-side resources in power system operations and market mechanisms, ultimately supporting a more resilient and efficient grid.

Table 1 provides a comparison of aggregated flexibility for a range of time periods, measured under different conditions: with grid conditions and without grid conditions. For each condition, flexibility is shown across three incentive scenarios: high, low, and no incentive. In the 'Without Grid Conditions' columns, flexibility values are typically higher, indicating the maximum theoretical flexibility available from consumers if grid constraints were not present. The 'With Grid Conditions' columns show adjusted flexibility values after considering grid constraints, which often result in lower values due to the technical limitations imposed by grid infrastructure, losses, and operational restrictions. These values highlight the impact of grid conditions on the effective flexibility that can be mobilized, especially during high-demand periods where flexibility with grid conditions is notably reduced. The table, therefore, illustrates how real-world grid limitations can significantly constrain the realized flexibility. The percentage variation in flexibility due to grid conditions fluctuates across different time periods, with some hours showing minor variations (~5-15%) where grid conditions may not be critical, while in other periods, variations exceed 50%, particularly in high-incentive scenarios, making grid constraints highly relevant for accurate realized flexibility estimation.

IV. Conclusion

This paper demonstrates the potential of aggregated consumer flexibility to enhance grid performance and support energy market participation under varying incentive conditions. Grid simulations with different flexibility scenarios show that high incentives lead to significant variations in flexibility, with grid constraints playing a crucial role on realized flexibility, as consumers adjust consumption significantly in response to price signals. In contrast, low incentives result in more moderate flexibility, while the baseline scenario underscores the importance of incentives for mobilizing demand-side resources. These findings highlight that responsive consumer behavior, driven by effective incentive mechanisms, can be a valuable asset for grid operators seeking to optimize load management and maintain system reliability. This approach provides a practical framework for quantifying the benefits of consumer flexibility, supporting the development of targeted strategies for a more resilient and economically efficient power system. The analysis also demonstrates that consumer flexibility significantly impacts grid losses and network security limits within the power network. By conducting sequential power flow simulations, we effectively quantified the influence of varying consumption patterns on the grid. The methodology allowed for the assessment of maximum, typical, and minimum flexibility scenarios. The results highlight that increased flexibility can lead to higher grid losses due to the additional strain on the network, underscoring the need to take grid constraints into consideration when forecasting available flexibility.

Acknowledgment

This article is a result of the Innovation Pact "NGS - New Generation Storage" (C644936001-00000045), by "NGS" Consortium, co-financed by NextGeneration EU, through the Incentive System "Agendas para a Inovação Empresarial" ("Agendas for Business Innovation"), within the Recovery and Resilience Plan (PRR).

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