Influence of Flexibility Modeling Parameters on Residential-Scale Demand Response Assessment

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***Abstract*—To incentivize residential-scale customer participation in explicit demand response (DR), it has to be possible to provide them with a sufficiently accurate assessment of the potential economic benefits they might gain from it. However, such an assessment necessarily requires good knowledge of the technical flexibility of the consumption and parameters characterizing it. In this study, a probabilistic DR assessment model is used to analyze the impact of various flexibility characteristics and constraints. It is found that some of them significantly affect the results, whereas others have miniscule influence. Furthermore, a case study based on a typical consumption profile allows to conclude that a householder without significant thermostatic loads has relatively small economic benefit from participation in explicit DR.**

***Index Terms*—demand response; flexibility; residential; sensitivity analysis; simulation**

I. Introduction

The European Union (EU) had already set itself ambitious targets for decarbonization and climate change mitigation, but on June 2018 a move was made to raise the aspirations even higher by envisioning a 32% share of renewable energy in the total consumption within the EU by 2030 [1]. However, the increasing adoption of renewable energy resources poses new challenges to successful and reliable operation of electric power systems. Some of the issues created by increased penetration of distributed and renewable energy sources (especially solar and wind) within power systems are caused by the stochastic nature of their energy production, i.e., frequency control and balancing issues, also power quality problems, which affect both power system real-time operation and the planning of future developments on the distribution grid as well as the transmission network level [2], [3].

While solutions to the emerging issues can be sought on the power generation, transmission or distribution side, the demand side also offers promising measures for mitigating the increasing stochasticity of power system operation [4]. Demand response (DR) has been identified as a particularly attractive tool power system operators could use for system services by offering incentives to consumers (so called explicit DR) [5], [6]. Furthermore, indirect encouragement of consumers to adapt their behavior for overall power system benefit by their voluntary exposure to electricity real-time prices or some other price-based programs (implicit DR) can bring some effect in coupling consumption patterns to generation availability [7], [8].

How widespread DR implementation can influence the operation of electric power systems is a subject already extensively studied in literature. While there are some associated risks identified (e.g., pronounced rebound effects with time-varying electricity prices [9]), most sources come to the conclusion that DR programs have the capability to reduce the overall power supply costs [10]–[13]. However, the economic effect of DR on the DR asset owners (i.e., householders or businesses with flexible load) is paid somewhat less attention to, some notable work being presented in [13]–[17]. Furthermore, in some cases, current market structures and incentives seemingly either fail to provide meaningful economic benefit to DR asset owners or only result in miniscule profitability [8], [18]–[20].

For sufficiently accurate assessment of the potential benefits a DR asset owner might gain by participating in either explicit or implicit DR programs, a detailed knowledge of their consumption flexibility and its characteristics is required. To that end, the authors of [21] offer an empirical methodology to obtain a full probabilistic characterization of residential consumers' flexibility. Their approach is based on quantile regression, but the findings suggest that there is potentially very high variability between different individual flexibility profiles. Furthermore, it is strongly dependent on factors like the number of occupants, baseline consumption and even the education level of consumers.

A flexibility indicator to be extracted from aggregate residential customer load patterns is proposed in [22]. It is found there that the flexibility levels become more prominent with decrease in customer aggregation. The authors of [17] also propose a specific parameter – flexibility ratio, which represents the average degree of flexibility in shifting an appliance within its operating time window. These studies, as well as [15], [16], [19] strive in favor of stochastic approach to demand flexibility assessment and DR modeling.

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Evidently, flexibility characteristics can be affected not only by technical, but also behavioral or even somewhat arbitrary factors. In this paper, we assess the effect certain flexibility metrics can have on the performance of a DR-enabled consumer participating in system balancing via explicit DR. This adds to the state-of-the-art by presenting a novel outlook to flexibility modeling specifically when the modeling purpose is the assessment of DR economic benefit from a householder's point of view.

II. Methodology

A. *Model*

The analysis in this paper utilizes an economic assessment model for DR presented in [23]. It is based on Monte Carlo simulations and involves generation of a large number of day-ahead price, balancing price, and balancing market liquidity scenarios and subsequent sequential simulation of DR activations for a whole year within each scenario ran in hourly resolution. The activations of DR depend on the demand for balancing (i.e., balancing market liquidity) as well as the hourly consumption and flexibility profile of the particular consumer or asset modeled.

Overall, the model structure can be summarized in four main blocks:

1. Electricity day-ahead price scenario generation;
2. Balancing market liquidity and price scenario generation;
3. Balancing activation simulations;
4. Annual economic assessment of DR profitability for the DR asset owner.

The day-ahead price scenarios are created for a whole year in hourly resolution. The random draw process is carried out on two levels. Firstly, the overall parameters for each scenario are selected from a normal distribution. These are: the mean price, the minimum and 'normal' maximum price, the maximum 'extraordinary' price peak, the expected ratios of weekend/weekday and daytime/nighttime prices, and the standard deviations of all these parameters. Secondly, the parameters drawn for each scenario are used to generate the hourly prices within it. The day-ahead prices are then used to construct time-varying retail prices by adding several other components to them: renewable levies, grid tariffs, trade commission and the value added tax.

The term "balancing market liquidity" here refers to the expected percentage of hours within a year when the power system operator seeks to activate the manual frequency restoration reserves (mFRR). Thus, the balancing market can have demand for either upward or downward balancing, or no demand for balancing within an hour. For those hours when balancing is required, the balancing price scenarios, are based on the expected ratio of upward or downward balancing price and the day-ahead price.

All the generated Monte Carlo scenarios are assigned equal realization probabilities. Once all the scenarios have been created, they are iterated through to simulate the DR activations subject to a number of conditions. The conditions that have to be met are as follows:

- the minimum time distance since the previous DR activation is respected;
- the number of DR activations in the current week does not exceed the limit;
- there is demand for upward balancing in the system;
- the DR asset has flexibility for load reduction during the particular hour;
- the balancing price falls within the DR asset's bid limits;
- there is enough flexibility in the next hours for DR energy recovery respecting the constraint for max duration before load recovery (relevant if the load recovery factor is nonzero).

The characterization of DR asset flexibility partially utilizes the terms illustrated in Fig. 1. Green color there denotes DR events, but red – the recovery effect in the opposite direction after a DR event.

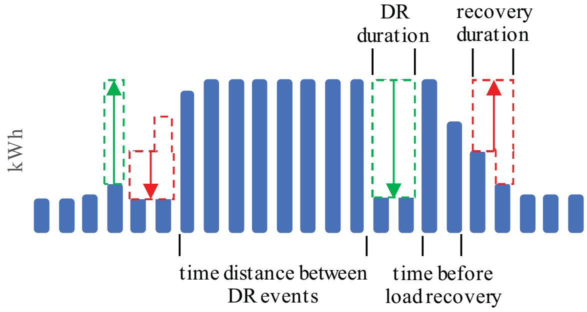

Figure 1. Explanation of some of the DR modeling terms used [23]

In this study, it is assumed that the load recovery does not necessarily need to have the same duration as the preceding DR activation. Instead, it is characterized by three different parameters: recovery energy (the DR energy multiplied by a set recovery factor), maximum duration before load recovery, which is the maximum time after the DR event that the beginning of the recovery can be postponed for, and the availability of flexibility in the necessary direction of load change. In essence, this models the phenomenon of load shifting, but in a somewhat unconventional way.

It should be taken into account that this study deals with an energy-based DR akin to the mFRR product used in the recently established Common Baltic balancing market [24]. Granted, the current regulatory framework is not favorable to DR participation in power system balancing in the Baltics, but for the purposes of this study, we assume it is legally and technically feasible, provided that the flexible assets are offered to the market in an aggregated manner. Additionally, we only consider upward balancing (i.e., load reduction) here.

The annual assessment of DR profitability is produced by calculating the cash flows associated with each simulated DR activation event. The sum benefit from a single event is calculated as in (1):

$$B = E_{\mathrm{DR}}^{tDR} \times \left(\Pi_{\mathrm{bal}}^{tDR} + \Pi_{\mathrm{ret}}^{tDR}\right) - E_{\mathrm{rec}}^{trec} \times \Pi_{\mathrm{ret}}^{trec}, \quad (1)$$

where E_{DR}^{tDR} is the reduced energy consumption due to a DR activation, which brings two positive cash flows – payment for balancing energy at balancing price Π_{DR}^{tDR} and reduced metered consumption during the event (at retail price Π_{ret}^{tDR}); however, the subsequent consumption increase (recovery effect, E_{rec}^{trec}) provides a negative component, as this energy has to be purchased at retail price $\Pi_{\mathrm{ret}}^{trec}$. The indices *tDR* and *trec* denote the set of hours when the DR and load recovery events, respectively, take place.

B. Sensitivity Analysis

The recovery factor in this study is defined as the ratio between the recovered energy and the DR energy. Essentially, this expresses energy savings (or conversely, efficiency losses) the customer achieves as a result of providing DR. Thus, the impact this setting has on the simulations is evident and it is not warranted to perform sensitivity analysis on it. The impact of several other flexibility modeling settings is, however, worth assessing. In this study, sensitivity analysis is performed for the following settings:

- minimum time distance between DR events;
- maximum time before load recovery;
- maximum number of DR events in a week;
- minimum duration of a DR event;
- maximum duration of a DR event;
- consumption flexibility (the percentage change of the hourly consumption which can be incurred due to DR activation or post-DR recovery).

The sensitivity analysis is carried out by repeated model runs wherein all the case study input data and model settings remain unchanged, except for the parameter to be analyzed, which is, instead, varied in a certain range. The impact of each parameter is thus assessed by comparing the simulation results, both the total economic benefit from DR and the specific benefit per unit of energy served in DR.

C. Case Study Data

Statistical parameters for day-ahead price scenario generation are derived from the historical prices in the Latvian bidding area of Nord Pool during the last 12 months at the time of performing these calculations – 01.11.2017–31.10.2018. Price scenarios are generated based on the following indicators: minimum price 1.59 €/MWh, the 99.5th percentile 100.06 €/MWh, maximum price 255.03 €/MWh, mean of the values up to the 99.5th percentile 45.81 €/MWh, mean ratio of weekday and weekend prices 1.21, mean ratio of daytime and nighttime prices 1.39. Subsequently, these are set as the scenario expected values with a 10% standard deviation for all of them.

The balancing market liquidity and balancing price generation settings are derived from the statistics of the recently established Common Baltic balancing market from 01.01.2018 until 31.10.2018. Expected balancing market liquidity for mFRR is 63.08% (i.e., demand for mFRR is expected in 63.08% of hours per year), ratio of hours with negative vs positive system imbalance 0.49, expected ratio of the day-ahead price vs balancing price at positive system imbalance (surplus) is 0.64 and at negative system imbalance (shortage) 1.87.

Furthermore, we assume that the DR asset owner is exposed to a dynamic retail tariff equal to the day-ahead price and affixed renewable support, trade commission and grid tariff components amounting to a total of 62.91 €/MWh fixed addition to the varying day-ahead price. Besides that, a value added tax (21%) is applied to the total sum of tariff components. Moreover, being a residential customer, the DR asset owner itself is not a balance responsible party.

Since the subject of this study is not a particular DR-enabled technology, we utilize an anonymized aggregated load profile of residential end-users from smart meter data library [25]. Since the model [23] allows for the representation of four distinct weekly load profiles, we generate different load profiles with the mean hourly consumption values (Fig. 2) and scale them to a maximum hourly consumption of 2 kWh, representative of an average-sized residential household in Latvia.

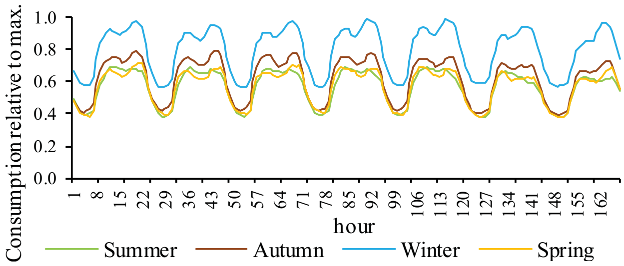

Figure 2. Weekly consumption profiles in different seasons

The flexibility at each hour is set in a simplistic manner by selecting a percentage from the hourly consumption which can be reduced for DR or increased for load recovery, the latter of which is constrained by the maximum consumption. Thus, instead of simulating specific home appliances (e.g., large thermostatic loads) we assume some flexibility in the overall consumption profile. Unlike [23], this study only considers load reduction DR, as it is a more realistic scenario for householder-scale DR. Thus, a portion of the total load is considered delayable. Furthermore, 10% energy savings during explicit DR activation are assumed, or, in other words, the recovery factor is set to 0.9, implying that not all of the consumption reduced during DR has to be recouped afterwards. This way we can model an effect resembling both load shifting and shedding, respecting the consumer flexibility bounds.

III. Results

A. Base Case

For the base case, let us test how profitable such an explicit DR program for power system balancing (mFRR) would be to a consumer with the assumed load (Fig. 2) and seemingly adequate flexibility modeling settings: minimum time distance between DR events – 0 (unconstrained); maximum time before load recovery – 12 hours; maximum number of DR events in a week – 14; minimum duration of a DR event – 1 hour; maximum duration of a DR event – 1 hour; consumption flexibility – 5%. The results of a model run with 1000 Monte Carlo simulations are summarized by probability distributions in Fig. 3 and Fig. 4.

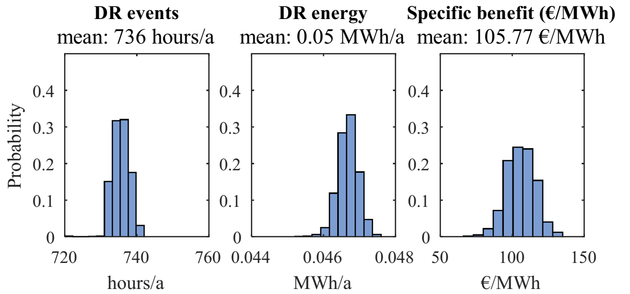

Figure 3. Probability distributions of simulated DR activations (*base case*)

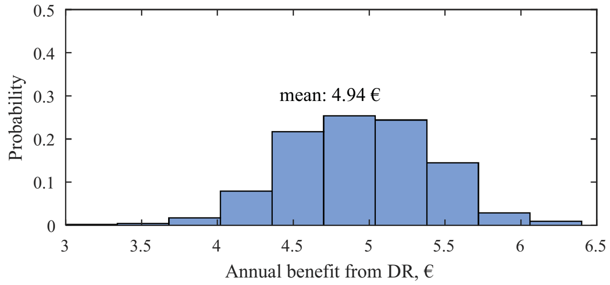

Figure 4. Probability distribution of the DR asset owner's annual benefit from DR (*base case*)

Evidently, in the base case, participation in explicit DR program provides very small benefit to the DR-enabled asset's owner. Furthermore, this calculation does not account for any variable or capital expenditure necessary to implement and maintain the DR capability. However, this is in line with some previous studies where the benefit from DR to residential load was estimated in single digits (e.g., 1 €/a for 2% load shifting or 6.5 €/a for 15% load shifting in [8]).

Furthermore, the energy provided to the TSO for balancing purposes is fairly small with the mean being only about 50 kWh annually. However, while such an amount of energy, of course, does not noticeably aid in power system balancing, the prior assumption was that this is only a part of a larger aggregated mFRR offer to the TSO. The scope of this paper envisions to look at the flexibility modeling and DR economic assessment issue strictly from the householder point of view, i.e., in a disaggregated manner.

B. Results of the Sensitivity Analysis

Results of the sensitivity analysis are summarized in Fig. 5–10, wherein the points corresponding to the base case are marked by a red cross. The average annual benefit in the simulated scenarios is portrayed with a blue line, whereas the average specific benefit per unit of energy served as DR for power system balancing is illustrated with an orange line.

Evidently, increasing the required minimum time distance between two explicit DR activations tends to decrease the annual benefit obtainable (Fig. 5). However, this effect is not so pronounced with the constraint values from 0 to 5 hours (with corresponding resulting benefit from 4.97 € to 4.88 €), beyond which the profitability starts to decrease more obviously. This can seemingly be explained by two factors. Firstly, the actual number of DR activations also decreases rapidly if the constraint is above 5, thus resulting in less total energy served in DR. Secondly, as the average specific benefit line portrays, the DR energy becomes less valuable the higher the constraint is. In fact, two distinct cases can be observed: if the minimum time distance constraint is in the range of [0; 5], the average specific benefit is roughly 106.00 €/MWh, but, in the range [9; 24], it is about 102.29 €/MWh.

As can be seen in Fig. 6, the constraint for maximum time before load recovery does not have a noticeable effect on either of the simulation result indicators. This is likely explained by the fact that the modeled consumption mostly always had sufficient flexibility in the direction opposite to DR in the next few hours following the DR event. Thus, the recovery effect could always start right after the DR event itself. In fact, this suggests that this constraint should be redefined to limit the time for completion of the recovery effect as opposed to the beginning of it. This would likely be far more useful in DR flexibility modeling, but a further study is necessary to confirm this assertion.

On the other hand, the next parameter analyzed, maximum number of DR events in a week, shows a lot clearer and straightforward picture (Fig. 7). Indeed, the more DR activations are allowed, the more remuneration is received resulting in an almost linear curve for the annual benefit. Evidently, this constraint is always active in the simulations, effectively designating the number of activations to be modeled. This arises from the fact that almost every modeled activation provides net positive benefit even if it is miniscule. If variable costs were taken into account and reflected in the bid price, the activations would be performed less often.

The specific benefit per unit of DR energy served (Fig. 7) also rises with higher maximum number of DR events in a week. However, it seemingly saturates at about 4 events a week. If relatively few activations are allowed, the likelihood increases of them being carried out in suboptimal time.

The impact of the next two parameters, minimum and maximum duration of a DR event, is summarized in the surface charts, Fig. 8 and Fig. 9. It should be noted that values of these constraints exceeding 1 are not realistic in the Baltic balancing market mFRR framework, but instead can denote hypothetical future purpose-specific flexibility markets for long-duration DR. Evidently, the most profitable case is when the minimum constraint is set to 2 hours and the maximum to 5 (Fig. 8). Conversely, the specific benefit is the highest when the minimum constraint is set to 1 and the maximum to 5 (Fig. 9). On the one hand, the wide temporal range of the DR event duration allows to increase the prospective profitability of DR, however, the longer a DR event is, the longer also the recovery period will be exposing the asset owner to more price volatility risks. The minimum DR event duration of 2 hours provides the best overall benefit likely because it balances the aforementioned long duration price variability risks with the overall higher DR energy that can be served compared to the case where the minimum duration is 1 hour but the number of activations per week limit remains the same. Thus, higher amounts of balancing energy provided by DR result in improved overall benefit despite lower specific benefit per balancing energy provided.

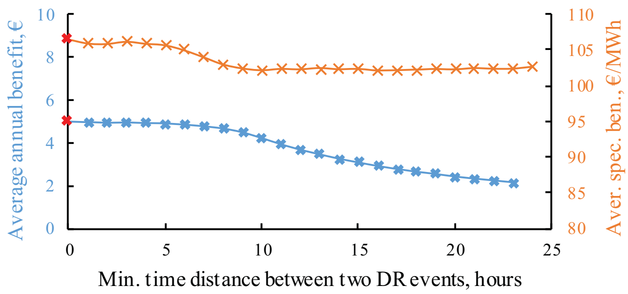

Figure 5. Sensitivity of model results to min time between DR events

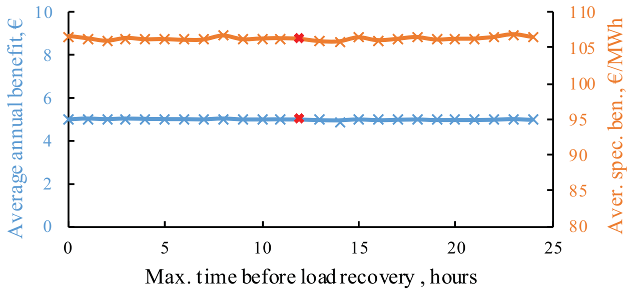

Figure 6. Sensitivity of model results to max time before recovery

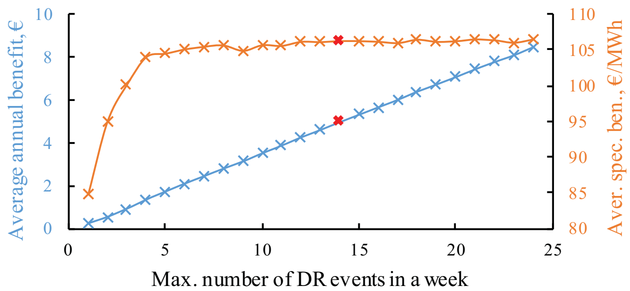

Figure 7. Sensitivity of model results to max activations a week

Finally, the last flexibility modeling parameter analyzed, the percentage of total consumption offered to DR, shows a nearly linear characteristic (Fig. 10). It follows that the more flexibility a DR-ready consumer offers, the more overall profitability they can expect. Of course, flexibility above the 5–15% mark is hardly realistic for a household, unless a significant part of their consumption comes from large thermostatic loads (e.g., electric heating) that have controllability potential. Nevertheless, these results being as expected aids in validating the overall performance of the model.

IV. Conclusions

The flexibility modeling parameter sensitivity analysis carried out in this study aids in validating the developed DR economic assessment tool and its capability to inform potential residential-scale DR participants on the potential activity and profitability from taking part in an explicit DR program. Moreover, this study confirms the importance of accurate selection of the parameter values describing the available flexibility of the consumption profile or particular flexible assets.

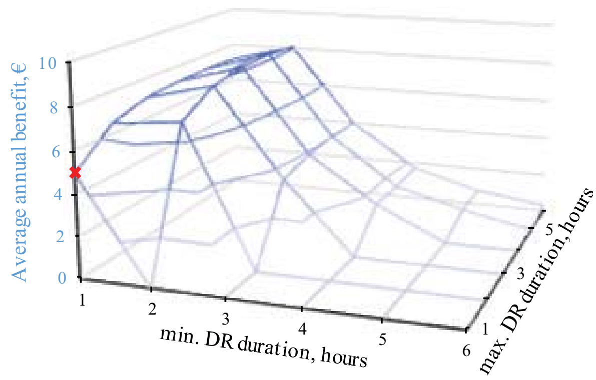

Figure 8. Annual benefit depending on DR event duration constraints

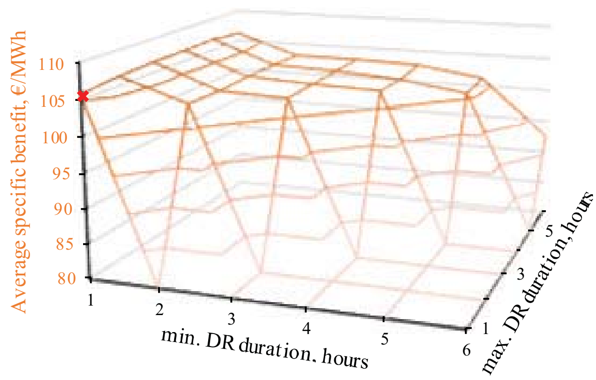

Figure 9. Specific benefit depending on DR event duration constraints

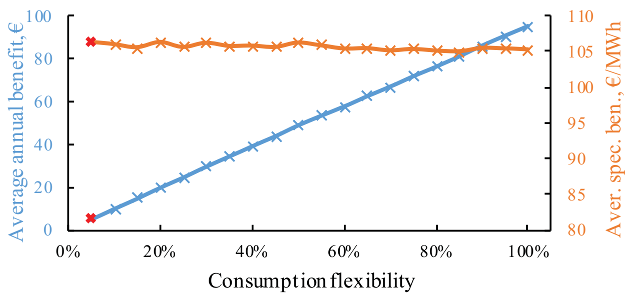

Figure 10. Sensitivity of model results to consumption flexibility

Metrics like the available flexibility within an hour, maximum number of DR events in a certain time horizon and the minimum time distance between two subsequent DR activations have to be selected particularly carefully as they majorly affect the model results. On the other hand, the maximum time before the beginning of recovery has proven to be inconsequential to the simulations and should instead be replaced by a constraint limiting the maximum time before the recovery has to be completed.

When the flexibility parameters are set to reasonable assumptions, it can be inferred that a residential-scale DR participant with a typical load profile, subject to electricity retail prices akin to the Latvian market and capable to participate in Baltic power system balancing (via an aggregator), can receive some annual benefit from explicit DR. However, with consumption flexibility of about 5%, the economic benefit is barely noticeable (about 5 € annum) and might not even offset the technical costs of DR readiness implementation and maintenance. Indeed, a householder with a typical standard consumption pattern without significant thermostatic load is not well incentivized to participate in explicit DR.

Further studies should aim to expand the DR assessment model to consider other potential markets and forms of explicit DR where residential-scale customers might theoretically participate in an aggregated form, since currently the model is focused solely on an mFRR product-based balancing market.

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