Analysis of the Potential Benefits from Participation in Explicit and Implicit Demand Response

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***Abstract*—In this paper, a Monte Carlo scenario-based model is utilized in analyzing the economic feasibility of participation in demand response (DR) from the perspective of a flexible consumption asset owner. Furthermore, the impact of implicit DR on the ability to provide explicit DR is assessed. Case study based on smart electric thermal storage heaters allows to conclude that implicit DR does not necessarily hinder the ability of providing ancillary services to the power system. Instead, it adds a supplemental benefit to the asset owner.**

***Index Terms*—balancing; demand response; flexibility; Monte Carlo; simulation**

I. Introduction

Demand response (DR) is deemed a potentially valuable tool for providing several benefits to power systems, e.g., balancing, renewable energy integration, spinning reserves, grid cost reduction etc. [1], [2]. While, in general, this topic is widely studied in recent literature in context of the ongoing transition to the Smart Grid paradigm [3], there is nevertheless still some uncertainty in terms of DR implementation.

While the reserve and regulating power markets do offer new and exciting possibilities for small consumers to participate in developing DR markets, the insufficiently clear rules regarding resource aggregation provide an apparent obstacle [1], [4]. Luckily, the situation is improving and policy-makers and power system operators throughout Europe are working on more efficient utilization of potential DR resources. For instance, it is increasingly viewed as an important and underutilized asset in the Baltic region [5], but the EU Clean Energy Package also calls for the involvement of demand side resources in all electricity markets.

However, participation in ancillary services (i.e., explicit DR) is not the only way to benefit from load controllability. Implicit DR, when consumers voluntarily adjust their consumption according to external price signals (e.g., optimizing load schedule as per hourly electricity prices), can also provide notable benefit [6], and the entry barriers are significantly smaller, e.g., no definitive need for aggregation. Technical capability to reschedule load and incentivizing tariff structure are the only requirements for implicit DR.

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The study presented in this paper aims to analyze the profitability of participation in both explicit and implicit DR from the perspective of the owner of flexible load assets on a householder level. Furthermore, it is tested whether price-based optimization of the flexible consumption schedule negatively affects the ability and profitability of participation in explicit DR, particularly focusing on the balancing market.

II. Methodology

A. Model Overview

For the analysis carried out in this study, a stochastic model for economic assessment of demand response based on Monte Carlo simulations was used. The tool has been introduced in [7] and relies on simulating the activation of explicit demand response assets for power system balancing purposes and calculating the cash flows therewith generated. The sequence of operations performed during a model run can be broadly summarized by the following steps:

1) day-ahead electricity market price scenario generation;
2) balancing market liquidity and price scenario generation;
3) balancing activation simulation carried out according to the consumer model and the generated scenarios;
4) annual economic assessment of DR profitability.

The day-ahead price scenarios are generated from settings describing the expected statistical parameters of the average scenario, i.e., mean price, expected ratios of weekday/weekend and daytime/nighttime means, the minimum price, the normal maximum price and the absolute maximum price for the right-side tail of the annual hourly price distribution, as well as the standard deviations for all these parameters, since for each scenario their values are drawn from a normal distribution.

The main inputs to generate the balancing market liquidity and price scenarios are the expected percentage of hours annually when the power system requires balancing which could be provided by aggregated DR assets, the expected ratio between upward and downward balancing calls, as well as the expected ratio between upward and downward balancing price versus the day-ahead market price at a respective hour.

Afterwards, all the scenarios are assigned equal realization probabilities.

B. *Assessing Benefit from Explicit DR*

The potential benefit from participation in DR is evaluated from the DR asset owner's perspective which is a residential customer with DR-enabled smart electric thermal storage heating installed at their household. It is assumed that, within normal operation, the asset owner pays a contracted dynamic price for the metered consumption, whereas DR activations and the subsequent recovery effect does not incur them imbalance penalties, as they themselves are not balance responsible. Thus the resulting benefit from a particular explicit DR activation can be calculated as in (1) for a load increase and (2) for a load reduction event [7]:

$$B^{\text{incr.}} = -E_{\text{DR+}}^{tDR} \times \Pi_{\text{bal}}^{tDR} + E_{\text{rec}-}^{trec} \times \Pi_{\text{ret}}^{trec}, \tag{1}$$

where $E_{\text{DR+}}^{tDR}$ is the increased energy consumption due to a DR activation during the set of hours tDR, purchased at the balancing energy price at that time Π_{bal}^{tDR}, and $E_{\text{rec}-}^{trec}$ is the energy consumption decrease in a subsequent time period $trec$ due to the recovery effect, purchased at the electricity retail price at that time Π_{ret}^{trec}.

$$B^{\text{red.}} = E_{\text{DR}-}^{tDR} \times \left(\Pi_{\text{bal}}^{tDR} + \Pi_{\text{ret}}^{tDR}\right) - E_{\text{rec+}}^{trec} \times \Pi_{\text{ret}}^{trec}, \tag{2}$$

where $E_{\text{DR}-}^{tDR}$ is the reduced energy consumption due to a DR activation, which brings two positive cash flows – payment for balancing energy and reduced metered consumption during the event; however, the subsequent consumption increase (recovery effect, $E_{\text{rec+}}^{trec}$) provides a negative component, as this energy has to be purchased at the retail price.

These same cash flow positions can be restructured in different components to explore particularly what effects produce the sum benefit. The considered effects are the benefit from the balancing market (3)–(4), the benefit from efficiency improvement (5)–(6) and, finally, the benefit from price variability (7)–(8):

$$B_{\text{bal.market}}^{\text{incr.}} = \left(\Pi_{\text{ret}}^{tDR} - \Pi_{\text{bal}}^{tDR}\right) \times \;\; {}_{\text{DR+}}^{tDR}, \tag{3}$$

$$B_{\text{bal.market}}^{\text{red.}} = \Pi_{\text{bal}}^{tDR} \times \;\; {}_{\text{DR}-}^{tDR}, \tag{4}$$

$$B_{\text{efficiency}}^{\text{incr.}} = \left(k_{\text{rec}}^{\text{incr.}} - 1\right) \cdot E_{\text{DR+}}^{tDR} \times \Pi_{\text{ret}}^{tDR} \tag{5}$$

$$B_{\text{efficiency}}^{\text{red.}} = \left(1 - k_{\text{rec}}^{\text{red.}}\right) \cdot E_{\text{DR}-}^{tDR} \times \Pi_{\text{ret}}^{tDR} \tag{6}$$

$$B_{\text{pr.var.}}^{\text{incr.}} = \left(\Pi_{\text{ret}}^{trec} - \Pi_{\text{ret}}^{tDR}\right) \times E_{\text{DR+}}^{tDR} \cdot k_{\text{rec}}^{\text{incr.}}, \tag{7}$$

$$B_{\text{pr.var.}}^{\text{red.}} = \left(\Pi_{\text{ret}}^{tDR} - \Pi_{\text{ret}}^{trec}\right) \times E_{\text{DR}-}^{tDR} \cdot k_{\text{rec}}^{\text{red.}}, \tag{8}$$

where $k_{\text{rec}}^{\text{incr.}}$ and $k_{\text{rec}}^{\text{red.}}$ are recovery coefficients signifying the proportion of energy utilized in DR to be recovered (by increased or reduced consumption) in subsequent hours. Essentially, it encodes the energy efficiency of explicit DR.

Note that only positions (3) and (4) can be ensured to be positive given an appropriate bidding strategy, whereas (5)–(8) can in some situations result in negative benefit (i.e. losses) if, for instance, the DR event causes efficiency decrease or if the retail price at recovery hours differs from the DR hour for the worse. However, the sum of these positions ought to be generally positive. Nevertheless, the overall profitability of participation in explicit DR also depends on the capital and operational expenditure (CAPEX, OPEX) related to the implementation and maintenance of the DR capability.

C. *Assessing Benefit from Implicit DR*

The equations (1)–(8) describe solely the benefit obtainable from participation in explicit DR programs for system balancing. However, it is reasonable to assume a consumer possessing some amount of consumption flexibility would primarily be interested in taking advantage of the time-varying electricity prices. For this purpose, the DR economic potential assessment model [7] has been enhanced with the ability to assess benefit from implicit demand response (i.e., purchasing electricity at dynamic hourly prices which are known the day before). In essence, sequential day-ahead optimization is performed for the whole year with the objective to minimize electricity purchase costs:

$$\sum_{t=1}^{24} \left(E_{\text{cons.}t}^{\text{unopt.}} + \Delta \quad {}_{t}\right) \cdot \Pi_{\text{ret.}t} \rightarrow \min, \tag{9}$$

subject to

$$E_{\text{flex.}t}^{\min} \leq \Delta E_t \leq E_{\text{flex.}t}^{\max}, \tag{10}$$

$$\sum_{t=1}^{24} \Delta E_t = 0, \tag{11}$$

where $E_{\text{cons.}t}^{\text{unopt.}}$ – the original, unoptimized energy consumption at hour t, ΔE_t (the optimization variable) – the change in hourly consumption for cost minimization, $\Pi_{\text{ret.}t}$ – electricity retail price at hour t, and $E_{\text{flex.}t}^{\min}$, $E_{\text{flex.}t}^{\max}$ – the lower (load reduction) and upper (load increase) bounds on the available consumption flexibility at each hour.

The constraint (11) ensures that the total daily consumption remains unchanged. The optimization problem (9)–(11) is clearly linear and can be solved with a simple linear programming approach.

If day-ahead rescheduling is modeled, the flexibility profiles available for balancing are readjusted accordingly before performing explicit DR activation simulations, but the overall consumption flexibility bounds remain the same, while the profile is changed as per the results of the price-based optimization. The annual benefit from implicit DR is estimated by contrasting the consumed electricity costs with and without rescheduling. For both explicit and implicit DR the resulting annual benefit is obtained in the form of probability distributions, since it accounts for all scenario results. Thus, the scenario mean is the expected benefit.

D. *Required Number of Scenarios*

The results of the model and their credibility strongly depend on the number of Monte Carlo simulations performed. However, evaluating a high number of scenarios can demand significant computational resources. Thus, a compromise between precision and evaluation time has to be found.

Fig. 1 illustrates the differences in results of model runs with varied number of scenarios (ten runs with each number to distinctly illustrate the dispersion of results). The green dots represent the deviation of each model result (expected benefit) from the overall average. The violet line, however, represents the mean calculation time of the runs.

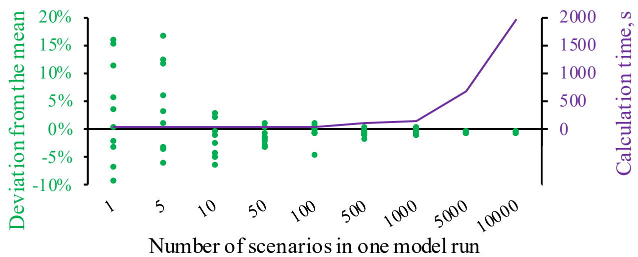

Figure 1. Tradeoff between calculation time and precision.

Evidently, 1000 scenarios are sufficient. They provide satisfactory low deviations (the highest value within the test runs – 1.31%) while still providing reasonable computational time (~153 seconds on an ordinary desktop computer). More simulations need significantly higher computational effort.

E. *Case Study Description*

The case study is based on thermostatic load, which has been identified in literature as one of the most promising load types for residential DR applications [8]–[10]. Particularly, we model smart electric thermal energy storage devices [11] able to receive external control signals (e.g., from an aggregator). The rated input power of each device is 2.2 kW, and we assume a household with five units installed. The default behavior (no gateway connection) envisions electricity consumption (i.e., storing thermal energy) in the first hours of each day, as the good thermal insulation of heaters allows the heat to be released when necessary throughout the day. Variable OPEX is disregarded in this study, but fixed OPEX is set to 20 € per annum.

Four different consumption and flexibility profiles for a week are used in the study to capture seasonal differences (the year is divided in four 3-month seasons). Heat energy demand is derived from building thermal modeling results in Riga, Latvia, suggesting that the average heat demand in spring is about 50% of the winter load, autumn – 20%, summer – 10%. In terms of flexibility, we assume any idle heater units can be turned on and any working units switched off for one hour up to 14 times a week if there is enough flexibility in the opposite direction for recovery to be completed within the next 12 hours. Summer is an exception – we assume only one additional heater unit can be turned on for load increase DR. The model has hourly resolution, and DR event duration is also set to one hour. The recovery effect is characterized by $k_{\text{rec}}^{\text{incr.}} = 0.9$ and $k_{\text{rec}}^{\text{red.}} = 0.9$, i.e., load increase DR results in slightly wasted energy, whereas load reduction DR manifests some energy savings.

The day-ahead price scenario generation is based on statistics in the Latvian price area of Nord Pool (01.11.2017–31.10.2018) and is summarized in Table I. A 10% standard deviation is set to these parameters during scenario generation.

TABLE I. DAY-AHEAD PRICE SCENARIO EXPECTED PARAMETERS

Day-ahead price scenario parameter	Expected value
Minimum price	1.59 €/MWh
Mean price (for 99.5% of hours)	45.81 €/MWh
Maximum price (for 99.5% of hours)	100.06 €/MWh
Maximum price (for 100% of hours)	255.03 €/MWh
Mean weekday and weekend price ratio	1.21
Mean daytime and nighttime price ratio	1.39

Parameters for balancing market scenarios are derived from the common Baltic balancing market data (01.01.2018–31.10.2018) and summarized in Table II. The market was launched on January, 2018 and has already proven to provide accurate and efficient system balance management [12]. The parameters from both tables are used to generate scenarios as per the algorithm described in [7].

TABLE II. BALANCING MARKET SCENARIO EXPECTED PARAMETERS

Balancing liquidity and price scenario parameter	Expected value
Balancing market liquidity (hours w demand for DR)	63.08%
Negative vs positive hourly system imbalance ratio	0.49
Balancing vs day-ahead price (at positive imbalance)	0.64
Balancing vs day-ahead price (at negative imbalance)	1.87

However, the owner of the flexible load purchases electricity for its regular consumption at a dynamic retail price defined as $\Pi_{\text{ret.}t} = 1.21 \cdot \left(\Pi_{\text{DA}} + 62.91\right)$, which is a representative electricity retail tariff in Latvia comprised of the hourly day-ahead wholesale price $\Pi_{\text{DA}t}$, trade commission (4.20 €/MWh), mandatory procurement component (14.63 €/MWh), distribution tariff (44.08 €/MWh) and a 21% value added tax on top. The consumption-independent monthly components of the tariff have been disregarded, as they would not be affected by DR.

For comparability, all the calculations within this study have been performed using the same 1000 scenarios for the day-ahead and balancing market (i.e., they have been generated only once). The distributions of the hourly prices generated are summarized in Fig. 2.

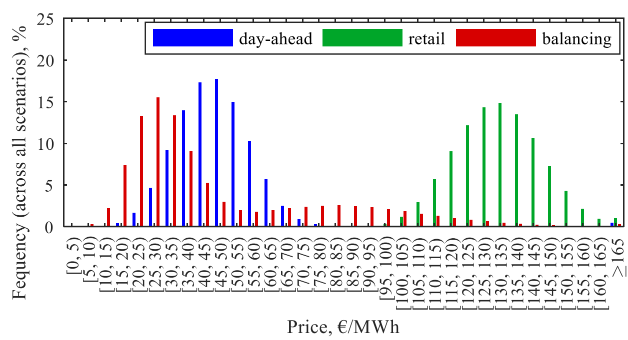

Figure 2. Histogram of electricity prices.

III. Results and Discussion

For comparison purposes, let us carry out two model runs. Firstly, with only explicit DR (for power system balancing, assuming aggregated DR capability to participate in the mFRR market in the Baltics) and, secondly, with additional implicit DR implemented by price-based rescheduling of the consumption on a day-ahead basis.

Fig. 3 summarizes the modeled scenario results in terms of the positive and negative annual cash flow positions incurred due to explicit DR activations for a case where the initial consumption has not been price-optimized. When compared to the same indicators for a case where there has been a day-ahead rescheduling performed beforehand (Fig. 4), three main implications can be inferred.

Firstly, the benefit from implicit DR is well comparable to that from explicit DR (e.g., 74.67 € from rescheduling, 336.16 € from balancing DR). Secondly, implicit DR does not negatively affect the profitability of participation in explicit DR but supplements it instead. Thirdly, the cash flow components directly dependent on the hourly retail price are most affected by the day-ahead rescheduling.

The same overall explicit DR benefit can also be expressed by its different components defined in (3)–(8). Fig. 5 and Fig. 6 provides the mean values (mathematical expectation) of these indicators.

While the mean overall annual benefit from explicit DR is slightly decreased (from 321.05 € to 316.15 €) if day-ahead optimization has been performed beforehand, the actual income from the balancing market is increased in the second case. However, it has been offset by the notably higher negative effect of the price variation component. It can be explained by the greater likelihood for the recovery effect post load-reduction DR to take place during high-price hours, since the initial pre-DR consumption is already placed at the cheapest hours in the second case. This becomes even more evident if we study the statistics of the modeled DR activations summarized in Table III.

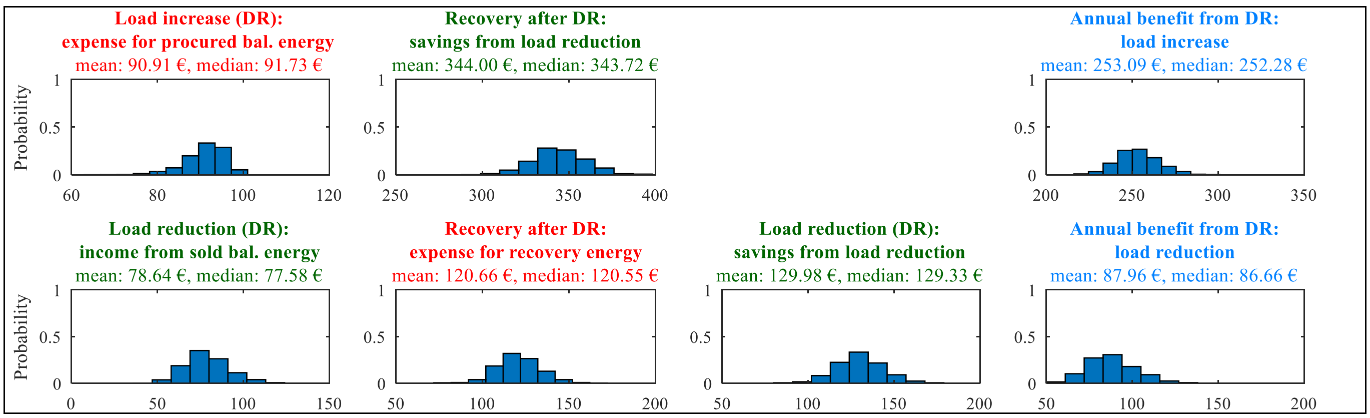

Figure 3. Probability histograms of the modeled cash flow positions (red – positive, green – negative, blue – total) without day-ahead rescheduling.

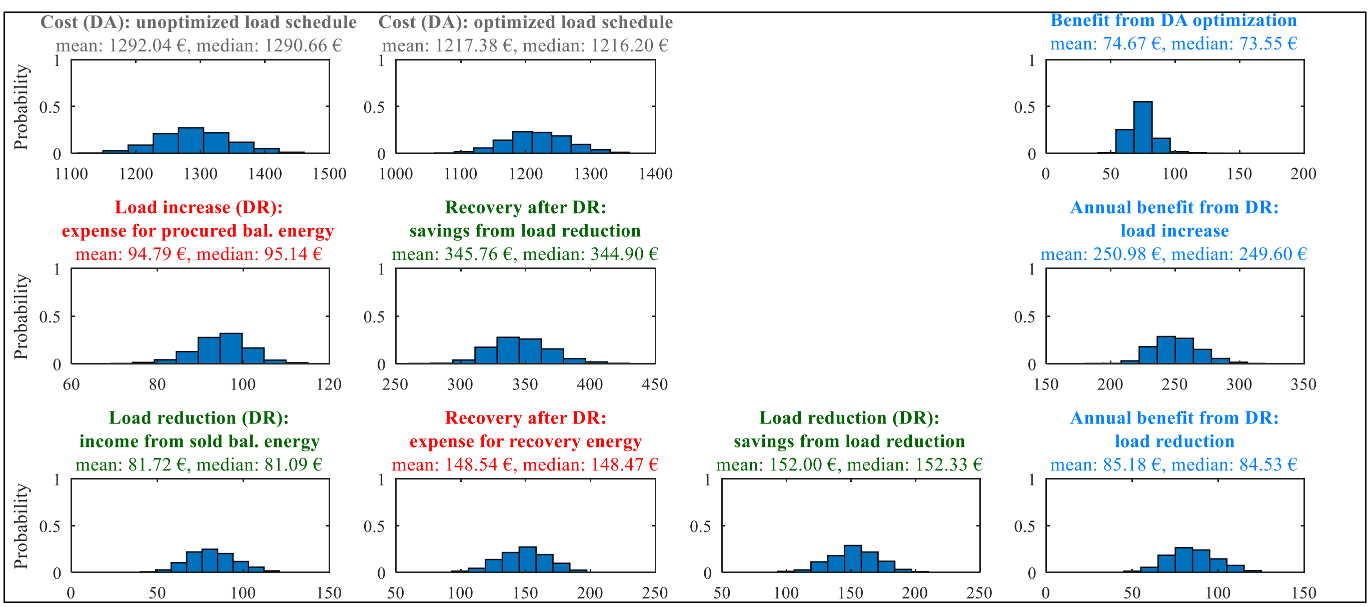

Figure 4. Probability histograms of the modeled cash flow positions (red – positive, green – negative, blue – total) with day-ahead rescheduling.

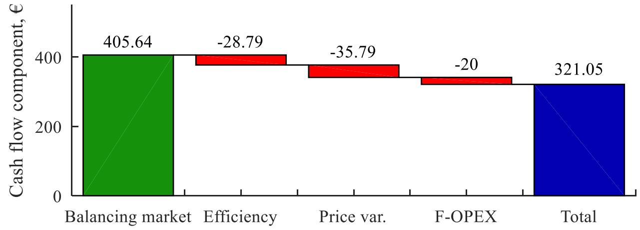

Figure 5. Breakdown of explicit DR mean total benefit (origin. schedule).

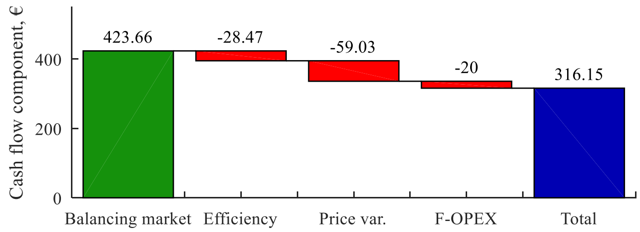

Figure 6. Breakdown of explicit DR mean total benefit (optim. schedule).

TABLE III. MEAN ANNUAL VALUES OF THE MODELED DR EVENTS

Case	DR events		DR Energy, MWh		Specific benefit, €/MWh	
	incr.	***red.***	***incr.***	***red.***	***increase***	***reduction***
origin.	431	222	3.13	1.04	80.95	84.60
optim.	386	154	3.26	1.30	76.97	65.44

Even though the total number of annual DR events has decreased (from 653 to 540 events) when the underlying consumption pattern of electric thermal storage heaters has been optimized, the sum amount of energy delivered for system balancing has actually increased (from 4.17 MWh to 4.56 MWh). Presumably, this is because post-optimization there are some hours with remaining flexibility only in one direction, and thus there are overall less hours when either directional DR is possible. However, the amount of flexibility in terms of energy in one direction is higher. The specific benefit per unit of energy served in explicit DR, however, is also decreased, notably so for demand reduction DR events.

If the asset owner were to incur notable variable OPEX due to energy served in explicit DR (e.g., loss of productivity, value of comfort lost etc.), the difference between both cases might become starker; however, this assertion remains to be studied. Some other significant assumptions that could influence the results is the balance responsibility of DR asset owner and prospective compensation to its retailer (for both, we assumed none), and it is also presumed that the payments to/from balancing market are equal to the respective balancing market price. If the DR asset owner were to pay additional taxes or share the benefit with its aggregator, the resulting profit would certainly be less.

IV. CONCLUSIONS

The DR economic assessment model explored in this study enables identification of benefits from explicit DR activation for system balancing purposes. It also allows studying the benefit by its components – balancing payment, efficiency increase (or decrease), and hourly price variations if a dynamic retail tariff is used. In the particular case study, the last two components provided a negative effect, albeit the sum cash flow remains positive and beneficial to the DR asset owner.

Furthermore, the analysis of smart electric thermal storage devices as an asset for explicit DR allows to draw the conclusion that being subjected also to implicit DR by means of price-based consumption rescheduling does not impede the overall profitability of explicit DR. While the parameters of DR activations and related cash flows do change, the sum benefit remains similar in both cases. Moreover, the exposure to implicit DR itself adds notable supplemental benefit to the overall profitability of DR-enabled smart electric thermal storage heaters.

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