

## Critical Analysis of the Profitability of Demand Response for End-Consumers and Aggregators with Flat-Rate Retail Pricing

Okur, Ozge; Voulis, Nina; Heijnen, Petra; Lukszo, Zofia

**DOI**

[10.1109/ISGTEurope.2018.8571538](https://doi.org/10.1109/ISGTEurope.2018.8571538)

**Publication date**

2018

**Document Version**

Accepted author manuscript

**Published in**

Proceedings - 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe, ISGT-Europe 2018

**Citation (APA)**

Okur, O., Voulis, N., Heijnen, P., & Lukszo, Z. (2018). Critical Analysis of the Profitability of Demand Response for End-Consumers and Aggregators with Flat-Rate Retail Pricing. In M. Kezunovic, & M. Selak (Eds.), *Proceedings - 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe, ISGT-Europe 2018* [8571538] Institute of Electrical and Electronics Engineers (IEEE).  
<https://doi.org/10.1109/ISGTEurope.2018.8571538>

**Important note**

To cite this publication, please use the final published version (if applicable).  
Please check the document version above.

**Copyright**

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

**Takedown policy**

Please contact us and provide details if you believe this document breaches copyrights.  
We will remove access to the work immediately and investigate your claim.

# Critical Analysis of the Profitability of Demand Response for End-Consumers and Aggregators with Flat-Rate Retail Pricing

Özge Okur\*, Nina Voulis†, Petra Heijnen\*, Zofia Lukszo\*

\*Energy and Industry, Delft University of Technology, Delft, The Netherlands  
Email: {o.okur, p.w.heijnen, z.lukszo}@tudelft.nl

†Systems Engineering, Delft University of Technology, Delft, The Netherlands  
Email: n.voulis@tudelft.nl

**Abstract**—Aggregators are considered essential to extend demand response (DR) to small residential and service sector consumers. Both sectors currently have untapped load flexibility, which is considered key to support renewable resource integration. Aggregators can offer this flexibility in bulk to other power system parties. This paper addresses the question under which conditions DR can be profitable for both aggregators and end-consumers. The paper builds further on existing research that shows end-consumer preference for flat-rate tariffs. The aim is to find the range of flat-rate retail prices for different photovoltaic (PV) feed-in-tariffs which make DR profitable for both aggregator and end-consumers. For this purpose, an optimisation model which minimises costs through load scheduling is presented. The model is applied using two approaches: optimising from aggregator’s and from end-consumers’ perspective. The results show that only the aggregator’s perspective yields a range of flat-rate retail prices that are profitable for both actors. However, both the price range and the expected profits of DR are small.

**Index Terms**—Aggregator, demand response, optimisation, pricing, renewable generation.

## NOMENCLATURE

### Parameters

$\lambda_t^{da}$	Day-ahead electricity price for buying and selling electricity at time $t \in \{1, 2, \dots, T\}$ [€/kWh]
$\lambda^{feedin}$	Feed-in electricity price for selling electricity [€]
$\lambda^{ret}$	Retail electricity price for buying electricity [€/kWh]
$P_{max}^{buy}$	Maximum power that can be purchased from the grid [kW]
$P_t^f$	Total energy consumption by flexible loads at time $t \in \{1, 2, \dots, T\}$ [kWh]
$P_t^{nf}$	Total energy consumption by non-flexible loads at time $t \in \{1, 2, \dots, T\}$ [kW]
$P_t^{PV}$	Solar generation at time $t \in \{1, 2, \dots, T\}$ [kWh]
$P_{max}^{sell}$	Maximum power that can be sold to the grid [kW]
$T$	Total number of hours
$t_{shift}$	Maximum shifting time [h]
<b>Variables</b>	
$C_{agg}^{da}$	Cost of the aggregator in day-ahead market [€]

$C_{agg}^{tot}$	Total cost of the aggregator [€]
$C_{cons}^{tot}$	Total cost of the end-consumers [€]
$P_t^{buy}$	Energy purchased at the day-ahead market at time $t \in \{1, 2, \dots, T\}$ [kWh]
$P_t^{scheduled}$	Scheduled energy consumption of flexible loads at time $t \in \{1, 2, \dots, T\}$ [kWh]
$P_t^{sell}$	Energy sold at the day-ahead market at time $t \in \{1, 2, \dots, T\}$ [kWh]
$P_{t',t}^{shifted}$	Loads shifted from time $t'$ to $t$ [kWh]
$y_t$	Binary variable indicating whether electricity is purchased/sold at time $t \in \{1, 2, \dots, T\}$

## I. INTRODUCTION

Demand response (DR) is considered a key component of future high renewables power systems. Renewable energy resources (RES) are weather-dependent and non-dispatchable. As energy storage is often still prohibitively expensive, demand-side flexibility is expected to become increasingly important to ensure the future power system remain balanced [1], [2]. However, incentivising demand response participation, in particular by small consumers, continues to be a challenge.

Historically, DR programmes were limited to a few large-scale industrial consumers [1], [3]. Recent progress in smart metering and advanced information and communication technologies opens the possibilities for DR participation by small service and residential consumers [4], termed “mass market demand response” [5]. However, as these consumers each represent only a small portion of the total demand, existing DR programmes designed for a few large-scale consumers cannot be simply extended to encompass mass market DR [1], [6].

To solve this issue, the creation of *aggregators*, a new market party who can coordinate mass market DR and offer combined DR services to other market parties, has been advocated by researchers (e.g., Hindi *et al.* in 2011 [7]). Currently, aggregators are indeed upcoming players in power markets [8]. Overall, aggregators can be seen as mediators between end-consumers and parties such as utilities and system operators [6]. They can provide the necessary upscaling which enables small consumers to participate in wholesale electricity markets [1].

Aggregators can thus resolve a number of challenges that existing market parties face. First, aggregators can increase the negotiation power of small consumers by representing them as one entity to existing large utilities and system operators. Second, aggregators can solve scalability challenges for system operators by decreasing the number of parties offering DR services. Third, aggregators can offer the knowledge and expertise in designing and deploying DR programmes, know-how the incumbents often lack [6]. Fourth, aggregators can engage otherwise unengaged customers and navigate power market complexities on their behalf [9].

The role of aggregators in future power markets, and their interactions with other market parties, is currently an active field of research [1]. As this is a developing field, a number of knowledge gaps still exist. First, most research focuses on residential load coordination (e.g., [1], [10]), leaving small service sector consumers such as offices, shops, restaurants, etc., out of scope. Yet, the load profiles in the service sector differ notably from the residential sector [11]. The service sector needs to be studied to evaluate the potential and the profitability of DR in the service sector. Second, a considerable amount of the existing work on aggregator-mediated DR addresses peak-shaving [10]. In future high-RES power systems, *residual* peak demand mitigation<sup>1</sup> is expected to be of far greater importance [12]. This paper addresses these knowledge gaps by (1) explicitly considering a realistic urban mix of residential and service sector consumers [11], and (2) explicitly modelling a high-RES future power system and taking residual load into account, instead of original load.

Building further on existing literature [10], this paper contributes to the understanding of profitability of aggregator-mediated DR, from the point of view of both end-consumers and aggregators. This profitability depends to a large extent on the pricing scheme offered by the aggregator, and the consumers' engagement in the DR programme. Both are currently active fields of research. Most of the proposed pricing schemes (e.g., time-of-use (TOU), critical peak pricing (CPP), and real-time pricing (RTP) [13]), require a relatively high effort from consumers, which can deter rather than entice participation [1]. Existing aggregator-mediated DR studies (e.g., [6]) typically require a frequent (for instance, daily) price negotiation between end-consumers and the aggregator, which arguably leads to social welfare maximisation, but similarly requires considerable effort from end-consumers. DR research and pricing research from other fields show that many consumers have a flat-rate bias, preferring simple pricing schemes, despite possible financial disadvantage [14], [15]. Therefore, this paper explores the DR profitability for both aggregators and consumers, assuming a high consumer participation under flat-rate electricity prices. Since high-RES scenarios are addressed, this paper assumes flat-rate prices for supply of electricity by end-consumers, similar to flat-rate prices for delivery of electricity. Such flat-rate supply prices

<sup>1</sup>Residual demand is defined as the difference between demand and "must-take" renewable generation [12].

can—from the consumers' perspective—be compared to feed-in-tariffs currently existing in many countries [16].

The aim of this paper is to find which flat-rate retail prices and solar PV feed-in-tariffs make demand response financially beneficial for both aggregators and end-consumers. Load scheduling of end-consumers' loads can be done either by the end-consumers themselves, or by the aggregator. In the first case, the aggregator merely provides market access. In the latter case, the aggregator has an additional active load management role. To distinguish these two cases, DR profitability is addressed from two perspectives: the aggregator's and the end-consumers'. Both cases are formulated as an optimisation model combined with realistic urban load, solar PV generation, and market data. The insights and results gained from this paper can be valuable for researchers, as well as for stakeholders such as end-consumers, aggregators, and policy makers.

The rest of the paper is structured as follows. Section II provides an overview of the system as well as the assumptions used. In Section III, the model equations are formulated and input data is outlined. In Section IV, the results are described and discussed, and finally, conclusions are drawn in Section V.

## II. MODEL DESCRIPTION

### A. System Overview

In this research, the aggregator participates in the day-ahead market (DAM) on behalf of residential and service sector end-consumers he represents. Some share of these end-consumers own photovoltaics (PVs). As depicted in Fig. 1, the aggregator purchases/sells electricity in the DAM with hourly day-ahead market price ( $\lambda_t^{da}$ ). On the other hand, the aggregator sells electricity to end-consumers with a constant retail price ( $\lambda^{ret}$ ) and buys excess solar generation of end-consumers with feed-in price ( $\lambda^{feedin}$ ).

In addition, the aggregator is given the permission to shift flexible loads within pre-specified limits. The only DR option considered in this study is load shifting, which refers to shifting of electricity consumption to another time period in response to electricity prices or abundant local electricity generation. The end-consumer loads can be classified into two types in terms of their controllability for load shifting purposes: flexible and non-flexible loads [17]. Loads which cannot be shifted without bringing discomfort to end-consumers are defined as non-flexible loads. Loads which can be shifted, such as refrigerators, heat pumps, fans, washing machines, dishwashers, and dryers, are regarded as flexible loads in this paper. In particular, heat pumps are included in this study, as they are expected to become key technologies as colder-climate countries electrify the heating sector [18]. Heat pumps are a special class of large thermostatically controlled loads (TLCs) alongside with for instance refrigerators. TLCs are considered essential loads for DR as they can store energy in the form of temperature gradients and their demand can be shifted without major loss of comfort [1].

This paper deals with the profitability of DR for both aggregators and end-consumers. The analysis in this paper provides insights in the range of flat-rate retail prices and

solar PV feed-in-tariffs that incentivise DR participation, while being financially beneficial for both the aggregator and the end-consumers. As each actor schedules the loads according to their interest, two approaches are shown: first, cost optimisation through DR by aggregators, and second, by end-consumers. Profitability of DR is defined in comparison to a reference case without DR.

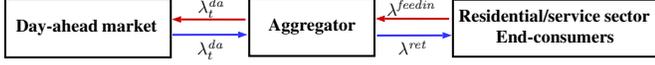


Fig. 1. Relations between actors in the system

## B. Assumptions

The results are based on the following assumptions:

- The aggregator has full information on the end-consumers' demand patterns.
- The aggregator competes with other aggregators and retailers on the existing power market, deriving their profit from load aggregation and flexibility services such as DR.
- The aggregator in this analysis is a price-taker with respect to the market prices, but by contrast a price-maker with respect to the retail price they charge their end-consumers.
- The aggregator only participates in the day-ahead market.
- The consideration of how to schedule the different devices is out of the scope of this paper. It is assumed that flexible devices are available for shifting, and the focus is on the profitability design space.

## III. PROBLEM FORMULATION

### A. Mathematical Formulation

In the first approach, the objective is to determine the optimal shifting strategy for the aggregator in the day-ahead market by scheduling the flexible loads, in order to minimise the aggregator's cost. This optimal scheduling problem can be formulated as a Mixed Integer Linear Programming problem in which the electricity cost in the DAM is minimised, based on electricity price and solar generation forecast. The symbols used here are given in the nomenclature section.

#### Aggregator's objective function:

$$\text{Minimise } \sum_{t=1}^T \lambda_t^{da} P_t^{buy} - \lambda_t^{da} P_t^{sell} \quad (1)$$

subject to

$$P_t^{buy} - P_t^{sell} + P_t^{PV} = P_t^{nf} + P_t^{scheduled} \quad \forall t \quad (2)$$

$$P_t^f = \sum_{t'=t-t_{shift}}^{t+t_{shift}} P_{t,t'}^{shifted} \quad \forall t \quad (3)$$

$$P_t^{scheduled} = \sum_{t'=t-t_{shift}}^{t+t_{shift}} P_{t',t}^{shifted} \quad \forall t \quad (4)$$

$$0 \leq P_t^{buy} \leq P_{max}^{buy} y_t \quad \forall t \quad (5)$$

$$0 \leq P_t^{sell} \leq P_{max}^{sell} (1 - y_t) \quad \forall t \quad (6)$$

$$0 \leq P_{t,t'}^{shifted} \quad \forall t \quad (7)$$

$$y_t \in \{0, 1\} \quad \forall t \quad (8)$$

The objective function in Equation (1) aims to minimise the cost of the aggregator for the participation in the day-ahead market, which is the sum of the cost of the aggregator buying electricity and the revenue obtained from selling surplus PV generation in the DAM. The power balance constraint in Equation (2) ensures that the demand from the end-consumers is satisfied by the supply at all times. Equation (3) describes that the flexible loads can be shifted forward and backward up to maximum shifting time ( $t_{shift}$ ) in order to limit discomfort for the end-consumers. Equation (4) calculates the total scheduled load at each hour shifted from other hours. The amount of power that can be purchased or sold in the day-ahead market is limited within the grid requirements in Equation (5) and (6). It should be noted  $y_t$  in Equation (8) is a binary variable which is equal to 1 if electricity is purchased and 0 if electricity is sold.

In the second approach, the objective function in Equation (1) is replaced by Equation (9) so as to minimise the cost of end-consumers. The constraints remain the same.

#### End-consumers' objective function:

$$\text{Minimise } \sum_{t=1}^T \lambda_t^{ret} P_t^{buy} - \lambda_t^{feedin} P_t^{sell} \quad (9)$$

This cost equation consists of electricity bought from the aggregator at the retail price and electricity sold to the aggregator at the feed-in price.

The cost of the aggregator in the DAM, the total cost of the aggregator, and the cost of the end-consumers are calculated for both approaches with the following equations:

#### Aggregator wholesale and total cost:

$$C_{agg}^{da} = \sum_{t=1}^T \lambda_t^{da} P_t^{buy} - \lambda_t^{da} P_t^{sell} \quad (10)$$

$$C_{agg}^{tot} = \sum_{t=1}^T \lambda_t^{da} P_t^{buy} - \lambda_t^{da} P_t^{sell} - \lambda^{ret} P_t^{buy} + \lambda^{feedin} P_t^{sell} \quad (11)$$

#### End-consumers total cost:

$$C_{cons}^{tot} = \sum_{t=1}^T \lambda^{ret} P_t^{buy} - \lambda^{feedin} P_t^{sell} \quad (12)$$

In Equation (10), the first term is the cost of the aggregator buying electricity from the DAM, whereas the second term is the revenue from selling surplus PV generation to the DAM. Equation (11) presents the total cost of the aggregator which includes the cost/revenue coming from the end-consumers in addition to the cost/revenue from the DAM. The total cost of the end-consumers is stated in Equation (12).

Using these equations, the cost of the aggregator and end-consumers ( $C_{agg}^{tot,ref}$  and  $C_{cons}^{tot,ref}$ , respectively) are calculated

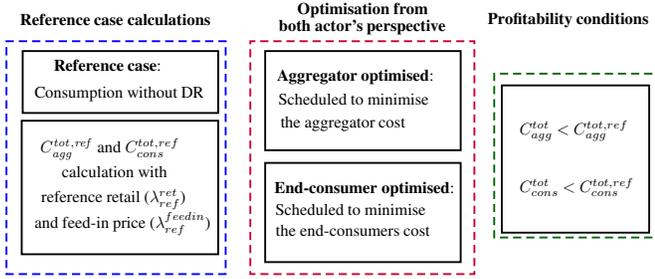


Fig. 2. Steps in the model

for the reference case. The reference case is defined as the situation without DR and with reference retail price ( $\lambda_{ref}^{ret}$ ) and reference feed-in tariff ( $\lambda_{ref}^{feedin}$ ). After the optimisation results from both perspectives, the cost of the aggregator and end-consumers are compared with  $C_{agg}^{tot,ref}$  and  $C_{cons}^{tot,ref}$  to find at which retail prices both actors could make profit. These steps are illustrated in Fig. 2.

The profitable retail price conditions for different feed-in tariffs are derived from the profitability conditions in Fig. 2 and given in Equation (13). According to these equations, the profitable retail price ( $\lambda_{prof}^{ret}$ ) should satisfy:

$$\lambda_{prof}^{ret} < \frac{\sum_{t=1}^T \lambda_{feedin}^{feedin} P_t^{sell} + C_{cons}^{tot,ref}}{\sum_{t=1}^T P_t^{buy}}$$

$$\lambda_{prof}^{ret} > \frac{\sum_{t=1}^T \lambda_{feedin}^{feedin} P_t^{sell} + C_{cons}^{tot,ref} + C_{agg}^{da} - C_{agg}^{da,ref}}{\sum_{t=1}^T P_t^{buy}} \quad (13)$$

The optimisation problem is implemented in GAMS using Mixed Integer Linear Programming and solved using solver CPLEX.

### B. Input Data

The model is evaluated for end-consumers in residential and service sectors separately. Since the demand profiles in residential and service sectors are different, the impact of these demand profiles on DR profitability is analysed. Different solar PV penetration scenarios are considered. Heat pumps are included in the model as a promising future source of DR. The Netherlands is used as case study. 1<sup>st</sup> of June 2012 until 31<sup>st</sup> of May 2013 is used as reference year, since measured household demand data is available for that period. The numeric results are based on the following datasets:

- *Residential demand profiles.* Measured household demand profiles of 63 households in the Netherlands are used. The breakdown electricity use along equipment-type is based on [19]. The total residential demand for the modelled year is 216 MWh, of which 34% is flexible.
- *Service sector demand profiles.* A realistic mix of service sector demand profiles is used, as described in [11]. Separate profiles for different equipment types are available. The total service sector demand is 230 MWh annual, of which 17% is flexible.

- *Heat pump demand profiles.* Electrification of heat is taken into account for both household and service sector consumers. Heat pump demand profiles are calculated as described in [20]. Heat pump penetration is assumed to be 50% in residential and service sectors and amounts to 158 MWh/year for residential consumers and 54 MWh/year for service sector consumers. As the annual demand for the two consumer types differs, results are expressed per MWh.

- *Wholesale electricity prices.* APX wholesale electricity prices are used.
- *Solar electricity generation profiles.* Solar power generation is calculated using the model by Walker [21], based on solar insolation data from the Royal Netherlands Meteorological Institute (KNMI) [22], and technical Solarex MSX-60 solar panel specification [23]. Three PV penetration scenarios are used for both consumers types: 25%, 50%, and 75% penetration, with respective annual generation of 53 MWh, 105 MWh and 158 MWh.
- *Retail and feed-in tariff prices.* The reference retail price is taken as the average retail price from the last 5 years in the Netherlands, which is equal to 0.1822 €/kWh [24]. In contrast to retail prices, a historical feed-in tariff cannot be taken from the Netherlands since it is not implemented. Hence, the retail price and feed-in tariff values from Germany are compared with the Dutch retail price and the reference feed-in tariff is taken as 0.06 €/kWh [25].
- *Shifting time.* The maximum shifting time for the flexible loads is assumed to be 2 hours based on [26].

## IV. RESULTS AND DISCUSSION

Fig. 3 (a) shows the average profile of original flexible loads in the service sector in June, together with how this flexible load profile is scheduled when optimised from the aggregator's and end-consumers' perspectives. Fig. 3(b) displays the average wholesale electricity price in June. In the aggregator optimised approach, the flexible loads are shifted to the hours with lower wholesale electricity price values in order to decrease the aggregator cost. Fig. 3 (c) shows the average solar generation in June. In the end-consumer optimised approach, the flexible loads are shifted to the hours when there is abundant solar generation since, in this way, end-consumers reduce the electricity bought from the aggregator. The conflict of interests between these actors can be observed from the differences in scheduling strategies.

Based on the optimisation results, the profitability of the aggregator and end-consumers is analysed from a multi-actor perspective. With the end-consumer optimised approach, there is no retail price that is profitable for the aggregator. With this approach, even though the cost of end-consumers drops, the aggregator gains less than the reference case in all scenarios analysed, which makes this not a profitable business case for the aggregator. Thus, the results from the end-consumer approach are not further addressed. Fig. 4 demonstrates the results from the aggregator optimised approach. This figure displays the retail price values that are profitable for both the aggregator and end-consumers for different feed-in tariffs in June. The shaded

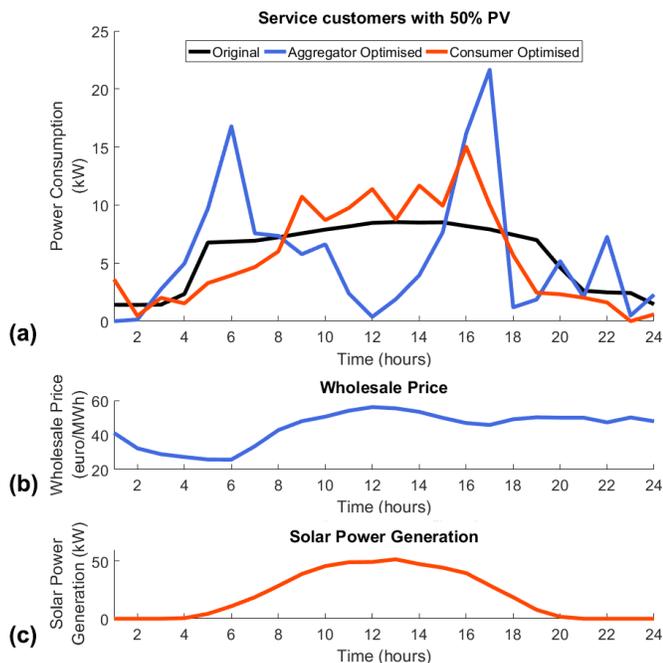


Fig. 3. Scheduling results for aggregator and consumer optimisation, average wholesale price, and PV generation in June 2012.

areas on the lines show the profitable retail price range and the darker lines show the midpoint of the range. The part above the line gives retail prices profitable only for the aggregator, while the part below is profitable only for the end-consumers. The results indicate that for each feed-in price, there is only a small range of retail prices that are profitable for both aggregator and end-consumers.

The general trend is that, as the feed-in prices increase, higher retail prices need to be offered as well for DR to be profitable for both actors. However, as PV penetration decreases, the retail price matters less. For instance, for the service sector consumers with 25% PV penetration, the aggregator could offer approximately the same the retail price with different feed-in tariffs. Additionally, for the same retail price, the aggregator has to pay higher feed-in tariff for the end-consumers with higher PV penetration for these consumers to be financially interested in DR.

The slope of service sector lines is flatter than residential lines. This can be explained by the differences in the load profiles of the residential and the service sectors. Residential consumption peaks in the evening hours, while service sector consumption primarily lies in the daytime hours. As shown in Fig. 3, aggregator-optimised load scheduling shifts demand to the cheaper evening hours. As the service sector has low demand during these hours, and the maximal shifting time is 2 hours, the service sector can provide less flexibility. This lower flexibility leads to relatively smaller interdependency between retail and feed-in prices for the service sector than for the residential sector.

A similar analysis is done for other months as well. In

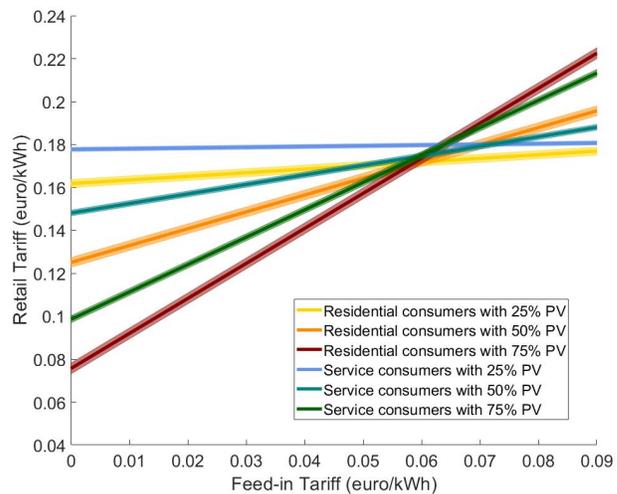


Fig. 4. Profitable retail prices for different feed-in tariffs for June 2012.

December, profitable retail prices are close to the reference price and do not differ significantly for different feed-in tariffs.

After the midpoint of profitable retail price range is found for each month, the yearly cost of the aggregator and end-consumers are calculated. Tables I and II present the cost of the aggregator, residential, and service end-consumers for one year in €/MWh. Reference retail with DR and profitable retail prices with DR for the same feed-in tariff are compared with the reference case (reference retail, without DR). How much the cost values changed compared to the reference case are also given in percentages in the parenthesis. Negative cost values imply profit. Similarly, negative percentages describe an increase in the profit. If the reference retail price is offered to the consumers when DR is performed, there is a substantial rise in total cost of end-consumers compared to the reference case. Accordingly, end-consumers are not incentivised to participate in DR.

However, when the profitable retail price is offered, the cost of end-consumers declines compared to the reference case and the aggregator makes profit at the same time as well. Therefore, it is shown that if the aggregator offers profitable retail price instead of the retail, both of the actors receive profit and DR is facilitated. Nonetheless, the cost of the end-consumers decreases only slightly. Comparing residential and service sectors in Tables I and II, the aggregator earns less in the service sector owing to less flexibility service sector provides. Thus, it appears to be a less profitable option in comparison to the residential sector.

## V. CONCLUSION

The results show that the profitability of the aggregator-mediated DR with flat-rate retail prices is very limited, even at very high consumer engagement rates. Comparing two optimisation approaches, with the end-consumer optimised approach, there is no profitable retail price for the aggregator. However, with the aggregator optimised approach, there is

TABLE I  
COST OF THE AGGREGATOR AND RESIDENTIAL END-CONSUMERS  
FOR ONE YEAR IN €/MWh

	Reference retail without DR	Reference retail with DR	Profitable retail with DR
End-cons. cost	131.7	136 (3.2%)	130.9 (-0.6%)
Aggregator cost	-95.7	-103.8 (-8.5%)	-98.7 (-3.1%)

TABLE II  
COST OF THE AGGREGATOR AND SERVICE END-CONSUMERS  
FOR ONE YEAR IN €/MWh

	Reference retail without DR	Reference retail with DR	Profitable retail with DR
End-cons. cost	117.9	119.7 (1.5%)	117.4 (-0.4%)
Aggregator cost	-88	-90.7 (-3.0%)	-88.4 (-0.5%)

only a small range where DR is profitable from a multi-actor perspective. Furthermore, even in that range, the decrease in the cost values is small. Similar analysis can be carried out with other types of pricing schemes. However, more complex pricing schemes, such as TOU, CPP, and RTP, require dedicated efforts from the aggregator to achieve and maintain high consumer engagement. The analysis in this paper is limited to the day-ahead market. Taking the balancing market into account could increase DR profitability. Multi-period DR optimisation is a subject for future work.

In a broader perspective, the results of this paper raise questions about the achievability of financially profitable flat-rate DR programmes for both aggregators as well as end-consumers. However, enhancing flexibility through DR is necessary to successfully integrate RES in the current energy system. Therefore, non-financial incentives and benefits can be considered for DR. For instance, Ito *et al.* discuss non-financial incentives such as “moral suasion” [27]. Alternatively, non-commercial aggregators can be considered.

#### ACKNOWLEDGEMENT

This work was supported by the Netherlands Organisation for Scientific Research (NWO) [grant number 408-13-012] and SES-BE program from STW Perspectief [project number: 14183].

#### REFERENCES

- [1] A. Rajabi, L. Li, J. Zhang, and J. Zhu, “Aggregation of small loads for demand response programs - Implementation and challenges: A review,” in *IEEE EEEIC and I&CPS Europe*, 2017.
- [2] T. Borsche and G. Andersson, “A Review of Demand Response Business Cases,” in *5th IEEE PES Innovative Smart Grid Technologies Europe*, 2014, p. 6.
- [3] J. Aghaei and M.-I. Alizadeh, “Demand response in smart electricity grids equipped with renewable energy sources: A review,” *Renewable and Sustainable Energy Reviews*, vol. 18, pp. 64–72, 2013.
- [4] P. Siano, “Demand response and smart grids—A survey,” *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, 2014.

- [5] P. Cappers, A. Mills, C. Goldman, R. Wiser, and J. H. Eto, “An assessment of the role mass market demand response could play in contributing to the management of variable generation integration issues,” *Energy Policy*, vol. 48, pp. 420–429, 2012.
- [6] L. Gkatzikis and I. Koutsopoulos, “The Role of Aggregators in Smart Grid Demand,” vol. 31, no. 7, pp. 1247–1257, 2013.
- [7] H. Hindi, D. Greene, and C. Laventall, “Coordinating regulation and demand response in electric power grids using multirate model predictive control,” in *IEEE PES Conference on Innovative Smart Grid Technologies*, 2011, pp. 1–8.
- [8] C. Eid, P. Codani, Y. Perez, J. Reneses, and R. Hakvoort, “Managing electric flexibility from Distributed Energy Resources: A review of incentives for market design,” *Renewable and Sustainable Energy Reviews*, vol. 64, pp. 237–247, oct 2016.
- [9] S. Burger, J. P. Chaves-Ávila, C. Battle, and I. J. Pérez-Arriaga, “A review of the value of aggregators in electricity systems,” *Renewable and Sustainable Energy Reviews*, vol. 77, pp. 395–405, 2017.
- [10] K. Vatanparvar and M. A. Al Faruque, “Design Space Exploration for the Profitability of a Rule-Based Aggregator Business Model Within a Residential Microgrid,” *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1167–1175, 2015.
- [11] N. Voulis, M. Warnier, and F. M. T. Brazier, “Impact of service sector loads on renewable resource integration,” *Applied Energy*, vol. 205, pp. 1311–1326, 2017.
- [12] J. Hu, R. Harmsen, W. Crijns-Graus, E. Worrell, and M. van den Broek, “Identifying barriers to large-scale integration of variable renewable electricity into the electricity market: A literature review of market design,” *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 2181–2195, 2018.
- [13] I. Lamprinos, N. D. Hatzigiorgiou, I. Kokos, and A. Dimeas, “Making Demand Response a Reality in Europe: Policy, Regulations, and Deployment Status,” *IEEE Communications Magazine*, vol. 54, pp. 108–113, 2016.
- [14] A. Lambrecht and B. Skiera, “Paying too much and being happy about it: existence, causes, and consequences of tariff-choice biases,” *Journal of Marketing Research*, vol. 43, no. 2, pp. 212–223, 2006.
- [15] E. V. Hobman, E. R. Frederiks, K. Stenner, and S. Meikle, “Uptake and usage of cost-reflective electricity pricing: Insights from psychology and behavioural economics,” *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 455–467, 2016.
- [16] A. Campoccia, L. Dusonchet, E. Telaretti, and G. Zizzo, “An analysis of feed in tariffs for solar PV in six representative countries of the European Union,” *Solar Energy*, vol. 107, pp. 530–542, 2014.
- [17] X. Ayón, J. Gruber, B. Hayes, J. Usaola, and M. Prodanović, “An optimal day-ahead load scheduling approach based on the flexibility of aggregate demands,” *Applied Energy*, vol. 198, pp. 1–11, 2017.
- [18] S. J. Darby, “Smart electric storage heating and potential for residential demand response,” *Energy Efficiency*, vol. 11, pp. 67–77, 2018.
- [19] J.-P. Zimmerman, M. Evans, J. Griggs, N. King, L. Harding, P. Roberts, and C. Evans, “Household Electricity Survey – A study of domestic electrical product usage,” Intertek, Tech. Rep., 2012.
- [20] M. Van Etten, “Simulating the flexibility potential of demand response with heat pumps in the Netherlands,” Master thesis, 2017.
- [21] G. Walker, “Evaluating Mppt Converter Topologies Using a Matlab Pv Model,” *Journal of Electrical Electronics Engineering*, vol. 21, no. 1, pp. 49–56, 2001.
- [22] KNMI, “Uurgegevens van het weer in Nederland,” <http://www.knmi.nl/klimatologie/uur-gegevens/selectie.cgi>. Last accessed online 17-01-2018.
- [23] Solarex, “MSX-60 and MSX-64 Photovoltaic Modules,” [www.solarelectricsupply.com/media/custom/upload/Solarex-MSX64.pdf](http://www.solarelectricsupply.com/media/custom/upload/Solarex-MSX64.pdf). Last accessed online 30-01-2018.
- [24] Centraal Bureau voor de Statistiek, “Aardgas en elektriciteit, gemiddelde prijzen van eindverbruikers,” <http://statline.cbs.nl>. Last accessed online: 30-01-2018.
- [25] Fraunhofer, “Recent Facts about Photovoltaics in Germany,” Tech. Rep., 2018.
- [26] P. S. Kwon and P. Østergaard, “Assessment and evaluation of flexible demand in a Danish future energy scenario,” *Applied Energy*, vol. 134, pp. 309 – 320, 2014.
- [27] K. Ito, T. Ida, and M. Tanaka, “Moral Suasion and Economic Incentives: Field Experimental Evidence from Energy Demand,” *American Economic Journal: Economic Policy*, 2017.