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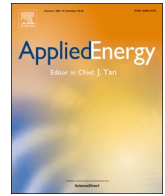
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# Aggregator-mediated demand response: Minimizing imbalances caused by uncertainty of solar generation



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## HIGHLIGHTS

- Demand response is used to address the uncertainty of solar generation.
- Forecast errors are modeled based on solar generation forecasts at different times.
- Model Predictive Control is formulated, incorporating solar generation forecasts.
- Demand response reduces the aggregator's individual imbalances.
- Aggregator is not financially incentivized to reduce individual imbalances.

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## ABSTRACT

The high level of uncertainty of renewable energy sources generation creates differences between electricity supply and demand, endangering the reliable operation of the power system. Demand response has gained significant attention as a means to cope with uncertainty of renewable energy sources. Demand response of residential and service sector consumers, when accumulated and managed by aggregators, can play a role in existing electricity markets. This paper addresses the question to what extent aggregator-mediated demand response can be used to deal with the impacts of the uncertainty of solar generation. Uncertain solar generation leads to imbalances of an aggregator. These imbalances can be reduced by shifting flexible loads, which is called demand response for internal balancing. The aim of this paper is to assess the impact of demand response from loads in residential and service sectors for internal balancing to reduce the imbalances of an aggregator, caused by uncertain solar generation. For this purpose, a Model Predictive Control model which minimizes the imbalances of the aggregator through load shifting is presented. The model is applied to a realistic case study in the Netherlands. The results show that demand response for internal balancing succeeds in reducing imbalances. Even though this is favorable from the power system's perspective, economic analysis shows that the aggregator is not financially incentivized to implement demand response for internal balancing.

## 1. Introduction

Increasing number of renewable energy sources (RES), such as wind and solar generation, results in both advantages and challenges for the power system. On the one hand, RES contribute positively to the reduction of greenhouse gas emissions, as well as to independence from fossil fuels. On the other hand, since the reliable operation of the power system requires a continuous balance between electricity supply and demand, the high level of uncertainty in RES generation poses serious challenges to the operation of the power system [1]. Any difference between electricity supply and demand causes a deviation of system frequency and reduces the quality of the electricity supply. Hence, it is

of great importance to avoid these differences, also called the *system imbalance* [2].

The growing RES penetration level in the power system requires novel sources of flexibility, including energy storage systems (ESS) and demand response [3]. Flexibility from ESS such as batteries, pumped hydro storage etc., is studied comprehensively in the literature [4]. Even though both demand response and ESS are regarded as crucial flexibility sources, in this paper we focus on demand response to cope with system imbalances caused by the uncertain generation of RES. Demand response (DR) is defined as changes in the electricity consumption of consumers from their normal consumption in response to external factors such as electricity prices and incentive payments [5].

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Nomenclature			
$N$	total number of hours	$P_{t,t''}^{sch,f}$	scheduled energy demand of flexible loads at run $t$ for PTU $t''$ where $t, t'' \in \{1, 2, \dots, T\}$ [kWh]
$T$	total number of Program Time Units (PTU)	$P_{t,t'}^{act}$	actual energy exchange (purchasing/selling) with the power grid at run $t$ for PTU $t'$ where $t, t' \in \{1, 2, \dots, T\}$ [kWh]
$t_{shift}$	maximum shifting time [PTU]	$\Delta_{t,t'}$	energy imbalances at run $t$ for PTU $t'$ where $t, t' \in \{1, 2, \dots, T\}$ [kWh]
$P_{t'}^{nf}$	energy demand by non-flexible loads for PTU $t' \in \{1, 2, \dots, T\}$ [kWh]	$\Delta_{t,t'}^+$	positive energy imbalances at run $t$ for PTU $t'$ where $t, t' \in \{1, 2, \dots, T\}$ [kWh]
$P_{t'}^{sf}$	energy demand by semi-flexible loads for PTU $t' \in \{1, 2, \dots, T\}$ [kWh]	$\Delta_{t,t'}^-$	negative energy imbalances at run $t$ for PTU $t'$ where $t, t' \in \{1, 2, \dots, T\}$ [kWh]
$P_{t,t'}^f$	energy demand by flexible loads at run $t$ for PTU $t'$ where $t, t' \in \{1, 2, \dots, T\}$ [kWh]	$y_{t'}$	binary variable for PTU $t' \in \{1, 2, \dots, T\}$
$P_{t'}^{da}$	day-ahead market energy bid with the planned energy exchange (purchasing/selling) with the power grid for PTU $t' \in \{1, 2, \dots, T\}$ [kWh]	$M$	a very large number
$P_{t'}^{PVfor,da}$	day-ahead solar generation forecast for PTU $t' \in \{1, 2, \dots, T\}$ [kWh]	$P_{t'}^{final,f}$	scheduled energy demand of flexible loads for PTU $t'$ , at the end of the model where $t' \in \{1, 2, \dots, T\}$ [kWh]
$P_{t,t'}^{PVfor,upd}$	updated solar generation forecast received at run $t$ for PTU $t'$ where $t, t' \in \{1, 2, \dots, T\}$ [kWh]	$\Delta_{total}$	total amount of imbalances for a day [kWh]
$P_{t,t',t''}^{shifted}$	at run $t$ , part of the original load from PTU $t'$ shifted to PTU $t''$ where $t, t'$ and $t'' \in \{1, 2, \dots, T\}$ [kWh]	$C_{total}$	total imbalance cost for a day [€]
		$\lambda_{t'}^+$	positive imbalance price for PTU $t' \in \{1, 2, \dots, T\}$ [€/kWh]
		$\lambda_{t'}^-$	negative imbalance price for PTU $t' \in \{1, 2, \dots, T\}$ [€/kWh]

However, DR from small consumers like residential and service sector consumers cannot resolve system imbalances caused by the uncertain generation of RES individually. They need to be aggregated and coordinated to have a substantial effect on the RES generation. This drives the need for aggregators. *Aggregators* are mediators between electricity customers, who offer DR, and electricity market participants who wish to exploit this DR [6]. To achieve this, aggregators participate in various electricity markets and offer DR from consumers in these markets to deal with uncertain generation of RES.

Considerable number of academic literature focus on eliciting DR from appliances such as washing machines, dryers, refrigerators, air conditioners, heat pumps, etc., owned by residential consumers. The work in [7] presents a quantified estimation of the flexibility of residential smart appliances for DR. The extent of flexible domestic demand in Great Britain in 2030 is analyzed in [8]. In addition, [9] studies optimal DR scheduling of loads in a residential community, coordinated by an aggregator. Very few authors and projects address DR from *service sector* consumers such as offices, shops, schools, etc., thus neglecting an important source of demand flexibility [10]. The present paper focuses on an aggregator with a portfolio including loads from both residential and service sectors and seeks to evaluate the realistic degree of potentially attainable DR in urban areas.

### 1.1. Electricity markets and imbalances

Balance between electricity supply and demand in the power system is achieved through electricity markets. Two electricity markets are considered in this paper: the day-ahead market and the balancing market. In the *day-ahead market* (DAM), market participants (including aggregators) submit their buying and selling energy bids, with the

electricity generation and demand forecasts for each hour for the day of delivery [11]. These DAM energy bids are submitted before the DAM closure time (12:00 noon in the Netherlands). After that, the market operator collects the bids of all market participants and determines a market clearing price for each hour of the next day based on these bids [12].

The second market considered in this paper is the *balancing market* which takes place in real-time during the day of delivery. The main time unit for the balancing market is Program Time Unit (PTU) which is equal to 15 min in the Netherlands [13]. The individual imbalances of market participants are calculated per PTU, in real-time. The *individual imbalance* is equal to the difference between the DAM energy bid and the actual energy exchange with the power grid in real-time [2]. Negative imbalances occur when participants have a shortage compared to the DAM energy bid, whereas positive imbalances occur when participants have a surplus compared to the DAM energy bid. The net sum of all individual imbalances of each of the market participants per PTU is equal to the system imbalance. Transmission System Operator (TSO) is responsible for eliminating the system imbalance and restoring the system balance.

The market participants in the balancing markets have a balance responsibility and are therefore called Balance Responsible Parties, meaning that they are financially responsible for their individual imbalances and are penalized with imbalance prices [14]. Thus, in the imbalance settlement process, which takes place after real-time, the individual imbalances are settled by means of imbalance prices. Fig. 1 illustrates a simplified representation of the timing of electricity markets and imbalances in the Netherlands. The participants with negative imbalances pay the negative imbalance price for each MWh of imbalance: the participants and with positive imbalances earn the positive

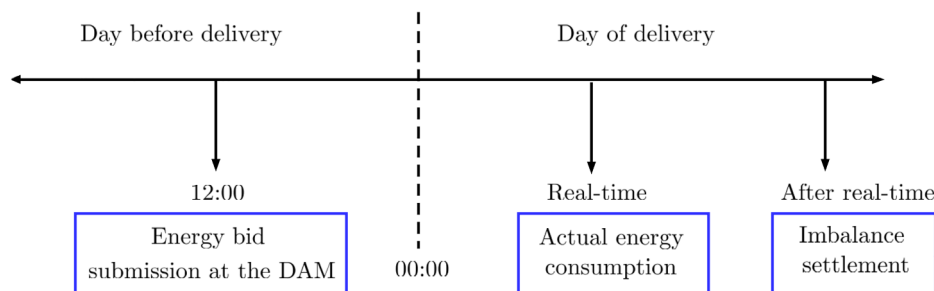


Fig. 1. Timing of electricity markets in the Netherlands.

imbalance price for each MWh of imbalance [2].

The participants are only financially incentivized to reduce their negative imbalances if negative imbalance prices are higher than what they would pay to buy the same imbalance amount in the DAM. Similarly, they are only financially incentivized to reduce their positive imbalances if positive imbalance prices are lower than what they would earn by selling the same imbalance amount in the DAM. By reducing the negative and positive imbalances, they decrease their individual imbalances. By decreasing the individual imbalances, the system imbalance is diminished as well. It should be noted that for several electricity systems a third market, the *intra-day market*, exists. Given the low liquidity of the intra-day market in the Netherlands, the intra-day market is not taken into consideration in this paper [13].

### 1.2. Internal balancing

Internal balancing can be defined as the real-time adjustment of electricity consumption within a portfolio so as to minimize the aggregator’s individual imbalance costs, adapted from [15]. In other words, the aggregator can use DR by shifting the loads in their portfolio to internally reduce the individual imbalance costs in real-time, without participating in any electricity market.

In the literature, a number of authors consider using different types of loads in real-time to reduce individual imbalance costs. In [16], an aggregator controls a group of storage space heating loads in the DAM and in the balancing market to minimize the imbalance costs. Similarly, [17] studies the DR aggregator’s participation in the DAM and balancing market with the objective of minimizing the aggregator’s DAM and imbalance costs. Thus, these papers focus on the aggregator’s participation in electricity markets, not their ability to carry out internal balancing. In [18], a market participant uses an industrial load, and a pumped-storage plant for internal balancing to minimize imbalance costs. These papers focus on minimizing the aggregator’s imbalance costs. Minimizing the imbalance costs of the aggregator is equivalent to solving an optimization problem from the aggregator’s point of view. In contrast, from the TSO’s point of view, the objective is to minimize the *system imbalance*. Unlike other papers, [19] aims to minimize the imbalances, regardless of prices. However, this is done using combined heat and power (CHP) plants where the output of CHP plants is scheduled and no aggregator is taken into account. To the best of our knowledge, little attention has been given to using DR from loads in residential and service sectors for internal balancing to minimize the individual imbalances of the aggregator.

The aim of this paper is to assess to what extent DR from residential

and service sector loads can be used for internal balancing to reduce the individual imbalances of the aggregators, caused by the uncertain generation of RES. Therefore, the scheduling of DR by the aggregator for internal balancing is studied to reduce their individual imbalances. For internal balancing, a Model Predictive Control model is employed.

### 1.3. Contributions of the paper

This paper contributes to the existing literature in three ways:

1. Assessment of DR to reduce the individual imbalances of an aggregator, caused by the uncertainty of solar generation.
2. An application of a state-of-the-art Model Predictive Control optimization model to minimize an aggregator’s individual imbalances.
3. A realistic case study based on data from the Netherlands: electricity demand from consumers in both residential and service sectors, solar generation forecasts at different time scales, and electricity market data.

The remainder of this paper is organized as follows. Section 2 provides an overview of the system considered in this paper. In Section 3, the model equations are formulated and explained. In Section 4, input data and some assumptions regarding the modeling choices are outlined. In Section 5, the results are described, and are discussed in Section 6. Finally, conclusions are drawn in Section 7.

## 2. System description

In this paper, the aggregator has residential and service sector consumers in their portfolio. Some consumers own solar photovoltaics (PV) panels. The aggregator is assumed to be an entity representing the role of a Balance Responsible Party, and a supplier of electricity to consumers. Hence, the aggregator participates in the DAM on behalf of the consumers. A more detailed explanation of these roles can be found in [20].

### 2.1. Load shifting for DR

The aggregator is assumed to be given permission to use consumers’ loads for DR within pre-specified limits for internal balancing. The only DR option considered in this study is load shifting, which refers to the shifting of electricity consumption to another time period. It is significant to point out that the success of load shifting for internal balancing depends on the consumers’ willingness to participate, which is to

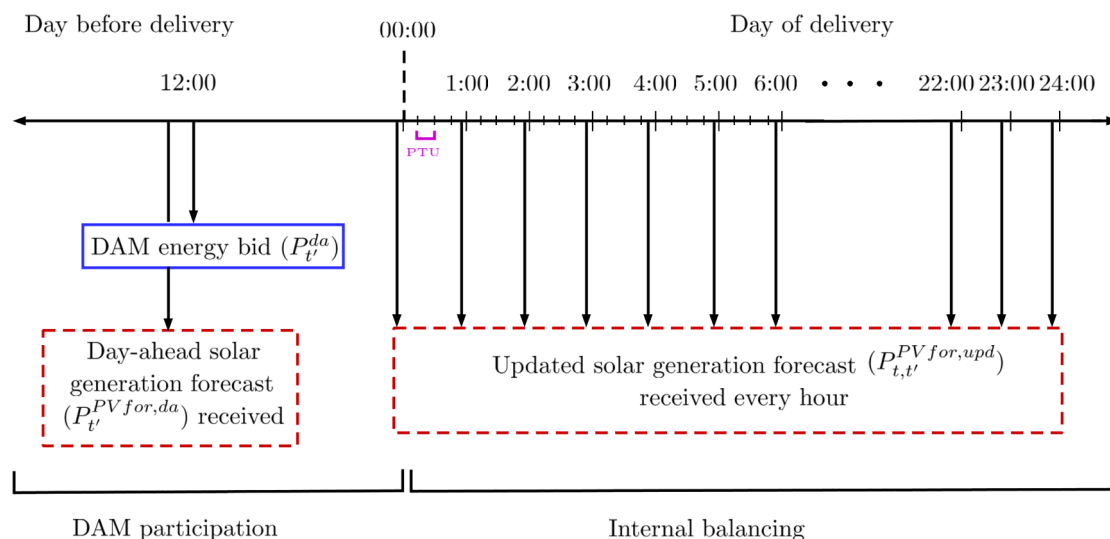


Fig. 2. Timing of DAM participation and internal balancing.

an important extent determined by the inconvenience caused by the load shifting. This inconvenience varies with the load and shifting time notice [21]. Specifically, different loads have different demand characteristics. Consequently, the consumers' loads can be classified into three types in terms of their controllability for load shifting purposes: non-flexible loads, semi-flexible loads and flexible loads.

- *Non-flexible loads:* Loads which cannot be shifted without bringing discomfort to consumers, such as televisions, computers and lighting.
- *Semi-flexible loads:* Loads that can be shifted without causing inconvenience to consumers provided that consumers are informed in advance. The shifting of these loads is suitable to be planned one day ahead. Some examples of these loads are washing machines, dishwashers, and dryers. We assume there are no semi-flexible loads available in the service sector, but only in the residential sector.
- *Flexible loads:* Loads that can be shifted within certain time limits on short notice without bringing loss of comfort to consumers such as refrigerators, freezers, heat pumps, fans and ventilation. The distinction in shifting notice time makes flexible loads more suitable for internal balancing. As a result, in this paper we assume that only flexible loads are available to the aggregator to be used for internal balancing.

### 2.2. Aggregator's DAM participation

The timing of the DAM participation and internal balancing is displayed in Fig. 2. Even though the DAM participation of the aggregator is not modeled in this paper, we assume that the aggregator takes part in the DAM by submitting the DAM energy bid before the DAM closure time (12:00 noon). The DAM energy bid includes the planned energy exchange with the power grid. The aggregator can purchase electricity from the DAM on behalf of consumers and can also sell excess solar generation of consumers in the DAM [22]. The DAM energy bid is based on DAM price predictions, consumers' demand predictions and day-ahead solar generation forecast. Day-ahead solar generation forecast is assumed to be received by the aggregator close to the DAM closure time and includes the prediction of solar generation for the day of delivery.

### 2.3. DR for internal balancing

On the day of delivery, once the DAM energy bid has been submitted, the intermittent characteristics of solar generation cause the aggregator to face deviations from the DAM energy bid. These deviations, caused by solar generation forecast errors, are the aggregator's individual imbalances. Note that, in this paper, the only cause of individual imbalances is assumed to be solar generation because the main focus is on dealing with the impacts of uncertain production of RES. Consequently, other possible causes of individual imbalances such as demand from consumers, electricity outages etc., are neglected.

The aggregator is assumed to receive updated solar generation

forecasts shortly before the beginning of every hour on the day of delivery, starting from 00:00, as illustrated in Fig. 2. These updated solar generation forecasts become increasingly accurate as the time horizon to real-time shortens [23]. Using a more accurate solar forecast, the aggregator can shift flexible loads shortly before delivery so as to minimize the imbalances, i.e., performing internal balancing. As expressed earlier, only flexible loads are available for shifting for internal balancing due to their controllability characteristics.

As the purpose of the aggregator in this paper is to minimize their individual imbalances, the positive and negative imbalances are not differentiated and they both need to be minimized. In this way, the aggregator intends to remain close to the DAM energy bid.

## 3. Optimization model

The aggregator is assumed to use an optimization model to implement DR for internal balancing. A Model Predictive Control (MPC) model is employed as the optimization model owing to its rolling horizon approach and its ability to update the model input. The objective of the MPC model is to minimize the total individual imbalances based on input data, some of which get updated between the different runs. The time resolution of the MPC model in this paper is PTUs which is 15 min in the Dutch balancing market. Since internal balancing starts at the beginning of the day of delivery (00:00), the MPC model starts at 00:00 and runs at every PTU until the next day (96 MPC runs per day).

The general algorithm for MPC, and its inputs and outputs to the MPC model for internal balancing are explained in the first subsection. The second subsection formulates the equations for the MPC model. The third subsection illustrates the use of the equations using a simplified example. The fourth subsection explains how to calculate the results for a single day from different runs of the MPC model.

### 3.1. Model Predictive Control

The basic algorithm for MPC can be summarized as follows. The MPC model aims to determine the optimal solution for the objective function, taking into account the constraints. This is done over a certain prediction horizon of T steps, starting from the current state of the system at the beginning of the time step k. After the optimal solution over the prediction horizon is found, the model implements the actions of the first time step of the prediction horizon. At the start of the next time step, the procedure is repeated. However, the prediction horizon is shifted and now starts at k + 1, and the model uses updated input data. Thus, the MPC model operates in a rolling horizon approach. More comprehensive information in the matter of MPC can be found in [24].

The MPC model in this paper is run at the beginning of each PTU (T = 96 times per day in total). The symbol t represents the MPC run, where  $t \in \{1, 2, \dots, T\}$ . The symbols t' and t'' denote the PTUs in that run. The inputs of the MPC model for different runs (Runs 1, 2 and 5) are illustrated in Fig. 3. The non-flexible, semi-flexible, flexible load demand from consumers ( $P_t^{nf}$ ,  $P_t^{sf}$ ,  $P_t^f$ , respectively), and the DAM

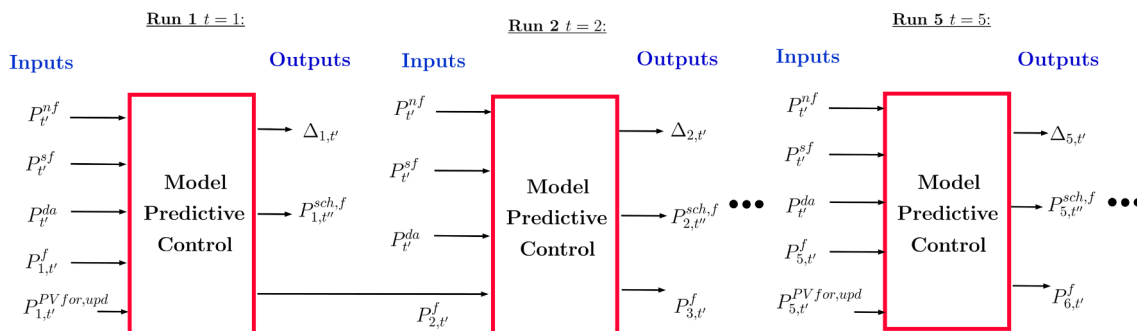


Fig. 3. The inputs and outputs of the MPC model for different runs (Runs 1, 2 and 5).

energy bid of the aggregator with the planned energy exchange with the power grid ( $P_{t'}^{da}$ ) are provided as the inputs to the model. In addition these inputs, updated solar generation forecasts ( $P_{t,t'}^{PVfor,upd}$ ) are also inputs to the model. Note that although the MPC model is run at every PTU, we assume that  $P_{t,t'}^{PVfor,upd}$  is received by the aggregator at every 4 PTUs. That is to say, the aggregator obtains an updated solar generation forecast shortly before the beginning of every hour.

It should be remarked that  $P_{t,t'}^f$  gets updated as a result of a MPC run, depending on how the flexible loads are shifted. Therefore, Fig. 3 shows that  $P_{t,t'}^f$  is obtained as the output of the current MPC run, and becomes the input for the next MPC run. Since its values might change between different runs  $t$  in the MPC model, the symbol is given as  $P_{t,t'}^f$ . Contrarily,  $P_{t'}^{nf}$ ,  $P_{t'}^{sf}$  and  $P_{t'}^{da}$  are input data that do not change between different runs;  $t$  is omitted in these symbols. Thus, for the inputs and outputs whose values change between different runs  $t$  in the MPC model,  $t$  is incorporated.

The outputs of the MPC model are also given in Fig. 3. As a result of every run of the MPC model, the optimal schedule of flexible loads ( $P_{t,t'}^{sch,f}$ ) which minimizes the total imbalances is acquired. Furthermore, the information regarding energy imbalance ( $\Delta_{t,t'}$ ), positive energy imbalances ( $\Delta_{t,t'}^+$ ) and negative energy imbalances ( $\Delta_{t,t'}^-$ ) are obtained as well.

### 3.2. Model Predictive Control formulation

The following MPC model is formulated.

$$\text{Minimize } \sum_{t'=t}^T \Delta_{t,t'}^+ + \Delta_{t,t'}^- \quad (1)$$

$$\text{subject to } P_{t,t'}^{act} + P_{t,t'}^{PVfor,upd} = P_{t'}^{nf} + P_{t'}^{sf} + P_{t,t'}^{sch,f} \quad \forall t', t'' \in \{t, \dots, T\} \quad (2)$$

$$\Delta_{t,t'} = P_{t'}^{da} - P_{t,t'}^{act} \quad \forall t' \in \{t, \dots, T\} \quad (3)$$

$$\Delta_{t,t'} = \Delta_{t,t'}^+ - \Delta_{t,t'}^- \quad \forall t' \in \{t, \dots, T\} \quad (4)$$

$$P_{t,t'}^f = \sum_{t''=\max(t'-t_{shift},t)}^{\min(t'+t_{shift},T)} P_{t,t',t''}^{shifted} \quad \forall t' \in \{\max(1, t - t_{shift}), \dots, T\} \quad (5)$$

$$P_{t,t'}^{sch,f} = \sum_{t''=\max(t''-t_{shift},1)}^{\min(t''+t_{shift},T)} P_{t,t',t''}^{shifted} \quad \forall t'' \in \{t, \dots, T\} \quad (6)$$

$$P_{t+1,t'}^f = P_{t,t'}^f - P_{t,t',t}^{shifted} \quad \forall t' \in \{\max(1, t - t_{shift}), \dots, T\} \quad (7)$$

$$0 \leq \Delta_{t,t'}^+ \leq My_{t'} \quad \forall t' \in \{t, \dots, T\} \quad (8)$$

$$0 \leq \Delta_{t,t'}^- \leq M(1 - y_{t'}) \quad \forall t' \in \{t, \dots, T\} \quad (9)$$

$$y_{t'} \in \{0, 1\} \quad \forall t' \in \{t, \dots, T\} \quad (10)$$

The objective function in Eq. (1) aims to minimize both positive and negative imbalances ( $\Delta_{t,t'}^+$  and  $\Delta_{t,t'}^-$ ) of the aggregator. Therefore, this equation gives the absolute value of the sum of the positive and negative imbalances. The power balance constraint in Eq. (2) ensures that the non-flexible, semi-flexible and flexible demand from the consumers are satisfied by the supply at all times: updated solar generation forecast and the actual energy exchange with the power grid ( $P_{t'}^{act}$ ). Eq. (3) calculates the total imbalance of the aggregator which equals the DAM energy bid subtracted from the actual energy exchange with the power grid. In Eq. (4), the total imbalance is broken down into the sum of the positive and negative imbalances of which at most one can be non-zero in one time step.

Eq. (5) describes that the flexible loads can be shifted forward and backward up to maximum shifting time ( $t_{shift}$ ) in order to limit the discomfort for the consumers. Eq. (6) calculates the total scheduled load at each PTU shifted from other PTUs. Eq. (7) determines the updated flexible load demand for the next runs.

Eqs. (8) and (9) make sure that the positive and negative imbalances are greater than or equal to zero and cannot occur at the same time, thanks to the binary variable  $y_{t'}$ . This binary variable  $y_{t'}$  is defined in Eq. (10) and is equal to 1 if there is a positive imbalance and to 0 if there is a negative imbalance.

It should also be noted that the equations are executed  $\forall t' \in \{t, \dots, T\}$  to incorporate the rolling horizon of the MPC model,

At run 1 ( $t = 1$ ):

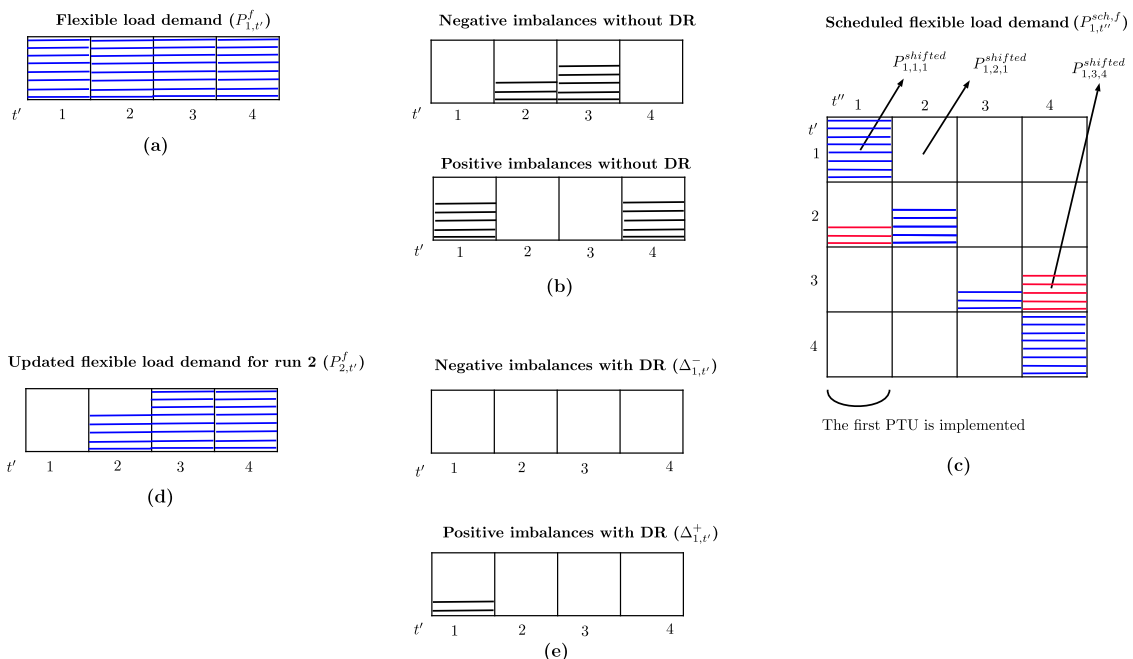


Fig. 4. The use of Eqs. (5)–(7) in a simplified example.

with the exception of Eqs. (5) and (7) as they are used to compute the updated flexible load demand which depends on the previous runs. The MPC model is implemented and solved in GAMS using the CPLEX solver.

### 3.3. Simplified example

The use of Eqs. (5)–(7) is demonstrated with a simplified example in Fig. 4. In this example, we assume that there are only 4 PTUs, and  $t_{shift}$  is 1 PTU. Besides, in Fig. 4, we present only the run 1 of MPC model ( $t = 1$ ).

Fig. 4(a) shows the original flexible load demand for the run 1 ( $P_{1,t'}^f$ ). The blue lines in this figure represent the original flexible load demand. In Fig. 4(b), the positive and negative imbalances without DR are given. In the MPC model, the flexible loads are shifted to minimize the sum of positive and negative imbalances according to the constraint in Eq. (5) and the objective function in Eq. (1). As a result of this MPC run, the scheduled demand of the flexible loads ( $P_{1,t'}^{sch,f}$ ) is computed based on Eq. (6) and presented in Fig. 4(c). The red lines in this figure denote the flexible load which is shifted to another PTU. As a result of this MPC run, the positive and negative imbalances ( $\Delta_{1,t'}^+$ ,  $\Delta_{1,t'}^-$ ) are reduced and given in Fig. 4(e).

After the MPC run, the first PTU is implemented. However, before the next run, the updated flexible load demand for the run 2 ( $P_{2,t'}^f$ ) is determined in accordance with Eq. (7) and depicted in Fig. 4(d). The load, that is shifted from PTU  $t' = 2$  to PTU  $t' = 1$ , is subtracted from the initial flexible load demand since the first PTU is already implemented. In a similar manner, the load, that is shifted from the PTU  $t' = 1$  to PTU  $t' = 2$  needs to remain for the second run as they are not served in the first PTU. Besides, for PTUs  $t' = 3$  and  $t' = 4$ , the flexible load demand remain the same since these PTUs are not implemented.

Note that Eqs. (5)–(7) are formulated in such a way that once a flexible load, which is originally to be served at PTU  $t'$ , is shifted from one PTU to another one, the same load cannot be shifted further than the  $t' + t_{shift}$ . Considering the same example as in Fig. 4, the parts of the load, which are shifted from the PTU  $t' = 1$  to the PTU  $t' = 2$  as a result of the first run, have to be served at the PTU  $t' = 2$  in the second run. These parts cannot be shifted further than the PTU  $t' = 2$ . However, the flexible load which is initially to be served at the PTU  $t' = 2$  can be shifted to the PTU  $t' = 3$ .

### 3.4. Calculations of the results for a single day

The MPC optimization model runs 96 times in a day, i.e. for all

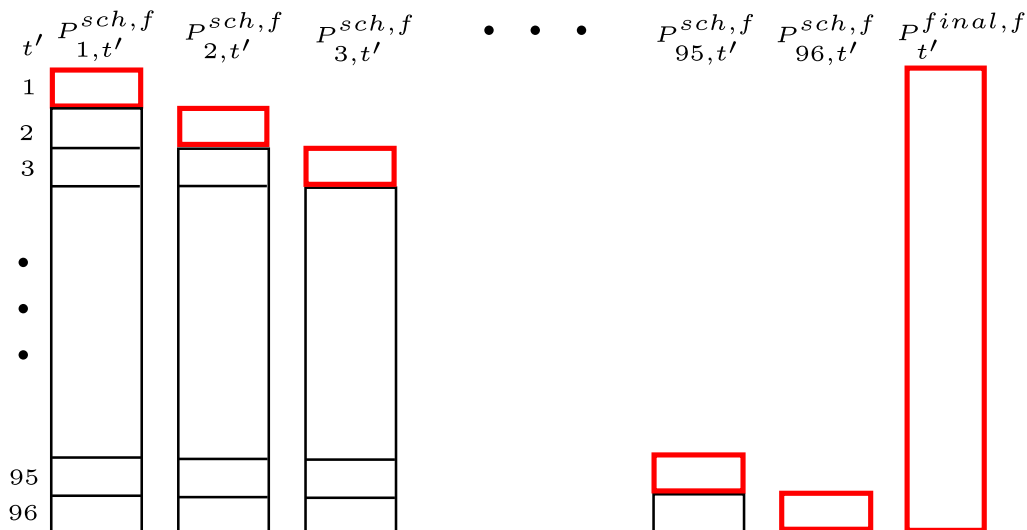


Fig. 5. Calculation of  $P_{t'}^{final,f}$  for a single day.

$t \in \{1, \dots, T\}$ . This means that the MPC model gives 96 sets of outputs in total. Due to the rolling horizon fashion of MPC, each next output starts from a later PTU  $t'$ . For instance, for the first run, the output  $P_{1,t'}^{sch,f}$  has 96 PTUs starting from  $t' = 1$ , while for the second run, output  $P_{2,t'}^{sch,f}$  has 95 PTUs, starting from  $t' = 2$ . This is illustrated in Fig. 5. However, in the MPC model, only the first PTU is implemented after each run. At the end of the model, the first PTU from each run should be taken as the result for a day, marked with red in Fig. 5. Therefore, the scheduled flexible loads at the end of the model ( $P_{t'}^{final,f}$ ) are defined as  $P_{t'}^{final,f} = P_{t',t'}^{sch,f}$  for  $t' \in \{1, \dots, T\}$ . The obtained vector is represented by the red rectangle on the right in Fig. 5.

The results for total amount of imbalances and total imbalance costs for a day are calculated from the outputs of each run in a similar manner. These calculations are presented in Eqs. (11) and (12). Eq. (11) describes the total amount of individual imbalances of the aggregator for one day as the absolute value of the sum of positive and negative imbalances. Total amount of individual imbalances is defined as the absolute value of this sum for the rest of the paper. Eq. (12) calculates the total imbalance cost of the aggregator for one day which consists of the cost from the multiplication of negative imbalance prices with negative imbalances, and the revenue from the multiplication of positive imbalance prices with positive imbalances.

$$\Delta_{total} = \sum_{t=1}^T \Delta_{t,t}^+ + \Delta_{t,t}^- \quad (11)$$

$$C_{total} = \sum_{t=1}^T \Delta_{t,t}^- \lambda_t^- - \Delta_{t,t}^+ \lambda_t^+ \quad (12)$$

## 4. Case study: Data & assumptions

The MPC model is implemented for a case study in the Netherlands. The input data for the case study, together with the assumptions regarding the modeling choices are described below.

### 4.1. Loads

The model is evaluated both for residential and for service sector loads. Electrification of heat is taken into account for both consumer types by assuming the use of heat pumps for heating. We assume that the aggregator has perfect knowledge on the load demands of the consumers. Hence, we do not model any uncertainty in load demand. Furthermore, the consideration of how to arrange the scheduling of

different devices separately is out of the scope of this paper. It is assumed that flexible devices are available for shifting. As discussed earlier, the only DR option considered in this study is load shifting. Thus, we assume that shifting loads does not change the total amount of electricity consumed.

- Residential demand profiles.** To model residential demand, the measured household data of 63 households in the Netherlands are used (data courtesy of the Dutch Distribution System Operator (DSO) Alliander). The data is available for the period from June 1st, 2012 until May 31st, 2013. This period is therefore used as the modeled year. The breakdown of electricity use in equipment-type is based on a British study [25]. Residential electricity demand characteristics for the Netherlands [26] are comparable with residential electricity demand characteristics for Great Britain [27]. The influence on variables such as income, family composition and type of dwelling on the demand profiles of the residential consumers is studied for the Netherlands in [28]. However, this is not considered in this paper as the demand profiles are aggregated by the aggregator, causing a reduction in the differences between the demand profiles. The total residential demand for the modeled year is 217 MWh, of which 142 MWh is non-flexible, 27 semi-flexible, and 48 flexible.
- Service sector demand profiles.** Service sector demand is modeled based on Commercial Building Models of the United States Department of Energy [29]. The shares of different service sector consumer types in the total service sector demand profiles represents a Dutch average and is based on [10]. Separate profiles for different equipment types are available for each service sector consumer type. The service sector demand profiles are scaled such that their total annual demand equals that of the residential demand modeled, 217 MWh/year, of which 180 MWh/year is non-flexible and 37 MWh/year is flexible. The annual demand for residential and service sectors is taken as equal to avoid any influence of the difference in the annual demand on the results.
- Heat pump demand profiles.** Electrification of heat is taken into account for both household and service sector consumers. Residential heat pump demand profiles are based on historic heating demand data of the same 63 households as used for modeling other residential loads (data courtesy of the Dutch DSO Alliander). Service sector heat pump demand profiles are based on the same Commercial Building Models [29] as used for modeling other service sector loads. Heat pump demand profiles are calculated from

historic space heating data as described in [30]. Heat pump penetration is assumed to be 50% in both residential and service sectors. This assumption leads to different annual demands by residential consumers (79 MWh/year) and service sector consumers (18 MWh/year). Fig. 6 demonstrates the annual and daily demand profiles in the residential and service sector, including heat pumps, in terms of percentage of total demand.

- Shifting time of the loads.** Based on the review of literature [21], the maximum shifting time for the flexible loads is assumed to be 2 h (8 PTUs) in the MPC model for flexible loads.

#### 4.2. Solar electricity generation profiles

Solar power generation is modeled based on solar insolation data from the Royal Netherlands Meteorological Institute (KNMI) [31]. These insolation data are converted to solar PV output using the algorithm developed by Walker [32] and technical specifications from Solarex MSX-60 PV panels [33]. It is assumed that 50% of the residential sector consumers own solar PV panels (1040 m<sup>2</sup> jointly), and that the service sector produces an equal amount of solar power per year (207 MWh/year). Uncertainty in solar power generation is considered by modeling solar generation forecasts based on historic data by Gaussian noise (i.e. error) addition to the measured historical data. The magnitude of the error increases with increasing forecast horizon. The method is described in [34]. The magnitude of the added errors depends heavily on the capacity of the power plant. The smaller the power plant, the higher the errors.

Two forecast scenarios are modeled: high and low forecast error. In the high forecast error scenario, the total capacity of the modeled solar PV panels for each consumer type is 0.1 MW. Given the small size of the joint solar PV panel area, the relative root mean squared error is taken to range from 25% for the next hour, to 40% for 24 h ahead of time. These values are based on a literature review of real solar forecasting models [35] and are thus representative of the real situation. In the low forecast error scenario, the errors are assumed to be five times lower, ranging from 5% for the next hour to 8.4% for 36 h ahead of time.

#### 4.3. Prices

In this paper, the aggregator is assumed to be a price-taker with respect to the DAM and imbalance prices. The model takes historic prices into account from the same period (June 1st, 2012 until May 31st, 2013) as the load data. Both the DAM and imbalance prices are

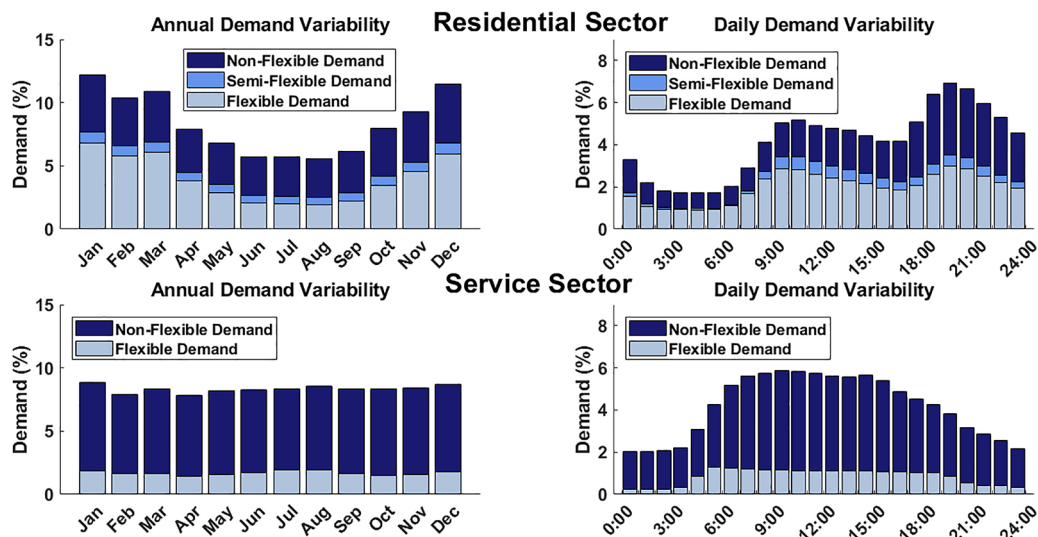


Fig. 6. Annual and daily demand profiles of the residential and service sectors. Left graphs illustrate the annual demand expressed as a percentage of total annual demand. Right graphs show average daily demand, with hourly demand given as a percentage of the total daily demand.



taken into account. For the DAM prices, historical EPEX wholesale electricity prices are used (data courtesy of the Dutch DSO Alliander). Imbalance price data are obtained from [36].

#### 4.4. Data granularity

The time resolution in the MPC model is 15 min. This data granularity is required to realistically model the Dutch balancing market. However, most data, with the exception of residential demand data, are only available with hourly granularity. Therefore, other loads, solar generation forecasts and actual solar generation data are interpolated as follows. For loads: for each quarter hour, corresponding hourly load data are divided by four. For solar generation forecasts: these are made with hourly granularity. Quarter hourly forecasts are obtained from hourly forecasts by dividing the forecast for each hour by four.

### 5. Case study: Results

This section presents results of the case study using the MPC model described in Section 3.

#### 5.1. Aggregator’s imbalances

Fig. 7 shows the reduction in the total amount of imbalances ( $\Delta_{total}$ ) for the months March, June, September and December with and without DR for internal balancing. This figure shows considerable seasonal differences. In December, the total amount of imbalances is the lowest. This can be explained by the fact that absolute solar generation forecast errors are smaller in this month due to lower solar generation. The total amount of imbalances is highest in June. In March and September, the total imbalances are comparable. Moreover, comparing the residential sector with the service sector, no considerable distinction between these sectors in terms of the total amount of imbalance reduction is observed.

Table 1 presents the maximum and the average reduction in the total amount of imbalances, as a percentage of the imbalances without DR for internal balancing. According to this table, for the residential sector in June, the aggregator’s total amount of imbalances can be reduced between 0% and 30%, with an average reduction of 8.7%. The minimum reduction in imbalances (0%) occurs when the imbalances cannot be reduced by DR for internal balancing. In December, the highest relative reduction in imbalances is achieved for both the maximum and the average values, in spite of the low total imbalances in December. This is caused by the small absolute forecast errors,

**Table 1**

Maximum (Max) and average (Avg) reduction of imbalances in different seasons and different consumer types, given as percentage of imbalances without DR for internal balancing.

	June		September		December		March	
	Max	Avg	Max	Avg	Max	Avg	Max	Avg
Residential	30%	8.7%	52%	9.1%	74%	15%	44%	12.1%
Service	39%	9%	48%	10.1%	74%	16.3%	45%	11.6%

combined with highest flexible load demand because of high heat pump usage in December, as illustrated in Fig. 6. Similar to Fig. 7, the results from the residential and service sector do not differ notably from each other.

#### 5.2. The impact of types of forecast errors

Table 1 shows that there is a large variation between the maximum and the average values each month. This is caused by the uneven reduction of imbalances over different days: imbalances can be decreased using the MPC model by a considerable amount on certain days, whereas on other days, the imbalance reduction is limited. The cause of this variation can be attributed to the types of forecast error. This is illustrated for four days in June. June 6th, 8th, 11th, and 25th are selected for this purpose, due to their different forecast characteristics. The results associated with these days are shown in Figs. 8–10.

In Fig. 8, the upper graphs show (1) the day-ahead solar generation forecast the aggregator received just before the DAM closure, and (2) the updated last available solar generation forecasts for internal balancing received on the day of delivery. The lower graphs depict the difference between them, called forecast errors. On June 11th, the day-ahead solar generation forecast overestimated solar generation for the entire day. In other words, the day-ahead forecast is greater or equal to the updated forecast for every PTU. Therefore, the forecast errors on this day are continually negative. This day is an example of a single-direction forecast error day. On the other hand, on June 8th, the forecast error switches its sign; it is positive at some PTUs and negative at others. June 8th and 25th show characteristics of a switching forecast error day. June 6th has smaller magnitude switching errors.

Fig. 9 presents the results for the scheduled flexible loads at the end of the model ( $P_i^{final,f}$ ), using the MPC model on the selected four days in June. The dark red lines in the upper four charts represent the original flexible load demand in the residential sector. The light red lines in the

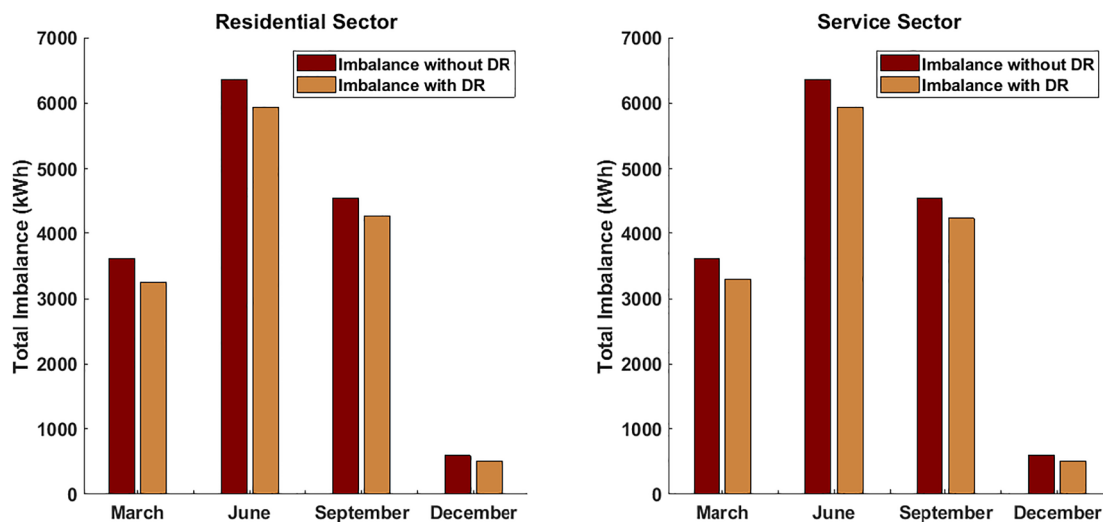


Fig. 7. Total amount of imbalances for March, June, September and December when DR for internal balancing is applied and when it is not applied.

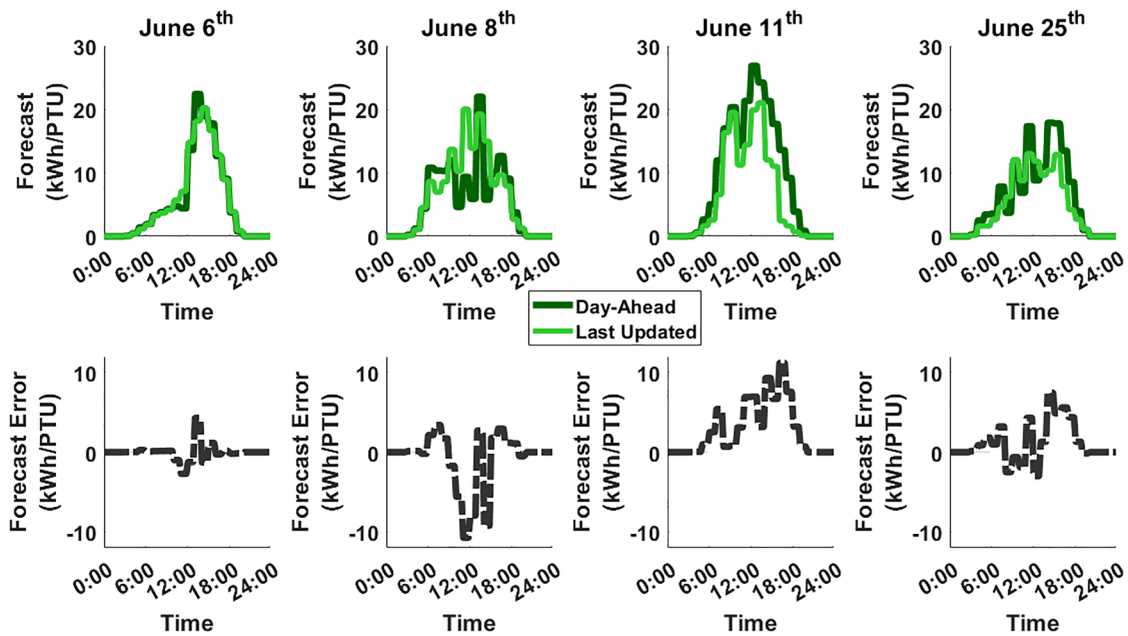


Fig. 8. Day-ahead solar generation forecast, updated solar generation forecast and the difference between them which is called as the forecast errors, for selected days in June.

upper four charts are the scheduled flexible load demand in the residential sector. Likewise, the dark blue lines in the lower four graphs indicate the original flexible load demand in the service sector. The light blue lines in the lower four charts represent the scheduled flexible load demand in the service sector. The flexible loads are only shifted from approximately 5:00 to 21:00 since there is no solar generation outside these hours, and thus no imbalances. On June 11th, the scheduled flexible load demand remains the same as the original flexible load demand in both the residential and service sector despite the large imbalances on this day. On the other days, the flexible loads are shifted to other PTUs to minimize the total imbalances.

Fig. 10 shows how the imbalances are reduced in residential and service sectors on the selected four days in June. The black dashed line

shows the imbalances without DR. The red and blue lines represent the imbalances with DR for internal balancing in the residential sector and the service sector, respectively. It is important to point out that the imbalance without DR is identical in both sectors as they are assumed to have the same area for PV panels and that the imbalances result solely from the solar generation forecast errors.

As shown in Fig. 10, the imbalances only occur from approximately 5:00 to 21:00 since there is no solar generation outside these hours. On June 11th, the imbalances remain the same for both residential and service sectors; the reduction in the total amount of imbalances on this day is equal to 0%. However, the imbalances are reduced on the other days. This means that the imbalances can only be decreased using DR for internal balancing if there are so-called switching forecast errors

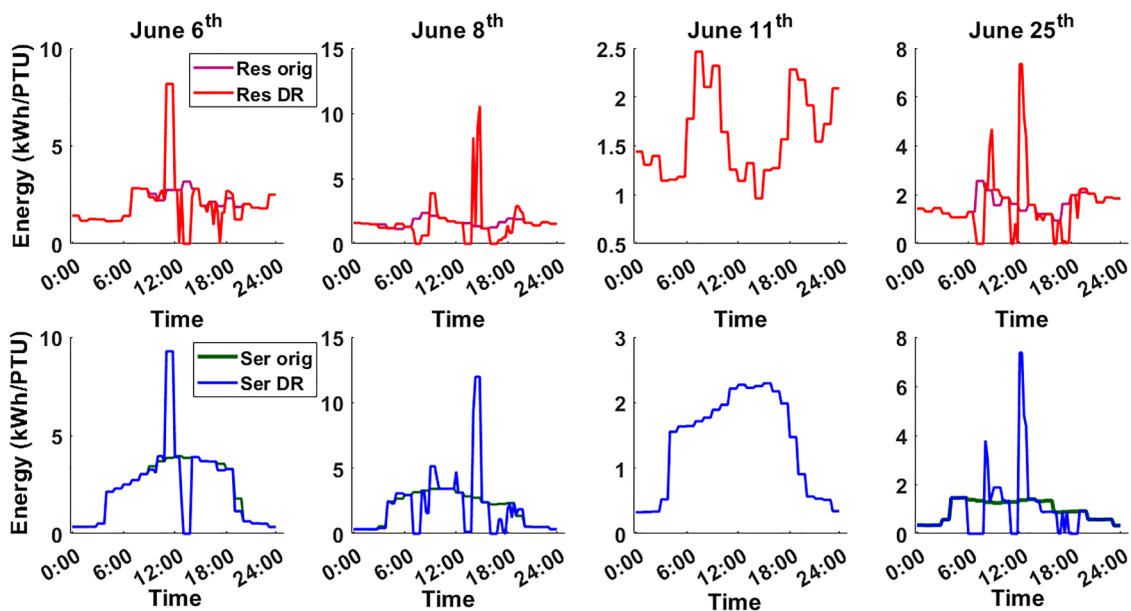


Fig. 9. The scheduled flexible load demand for selected days in June. The upper four graphs illustrate the original flexible load demand and the scheduled flexible load demand in the residential sector (Res). The lower four graphs show the original flexible load demand and the scheduled flexible load demand in the service sector (Ser).

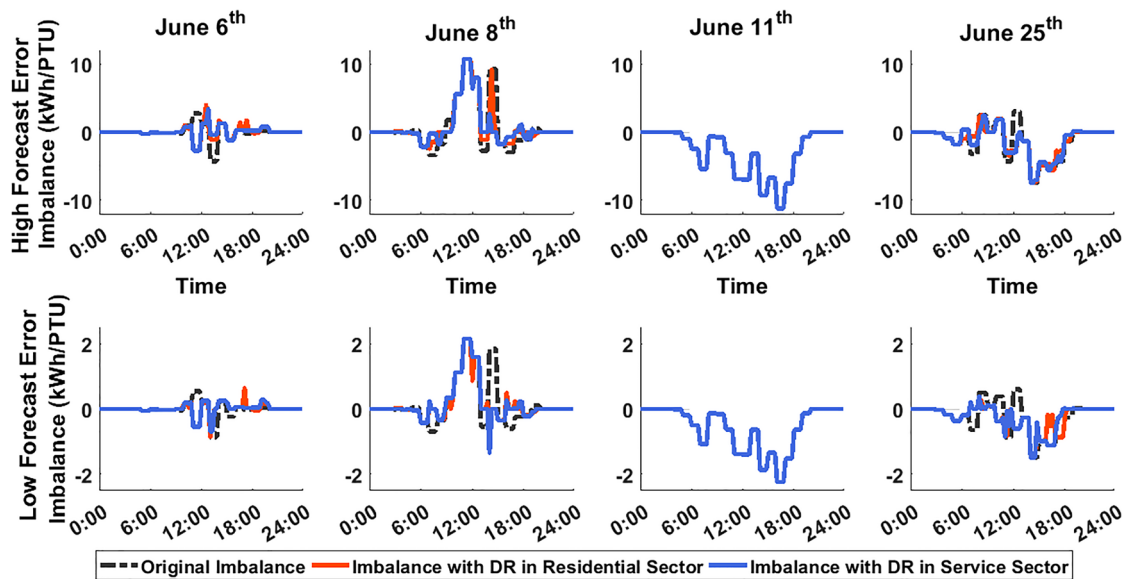


Fig. 10. The total amount of imbalances in the residential and service sector for selected days in June. The upper four graphs depict the total amount of imbalances with and without DR in residential and service sectors with *high forecast errors*. The lower four graphs show the total amount of imbalances with and without DR in residential and service sectors with *low forecast errors*. (Note the difference in scale on the y-axis.)

within the same day, as might be expected. On these switching error days, the flexible loads can be shifted from the PTUs with underestimation of solar generation to the PTUs with overestimation of solar generation. In contrast, on single-direction error days, DR for internal balancing cannot resolve the imbalances since solar generation is overestimated or underestimated for the entire day. However, it cannot be known to the aggregator in advance whether the day will be a switching error or a single error day.

5.3. The impact of magnitude of forecast errors

To gain understanding of the impact of the magnitude of forecast errors on the imbalance reduction, the same analysis is carried out for the same selected days in June, but with a smaller magnitude of forecast errors: low forecast error scenario. The results from this analysis are depicted in the lower graphs of Fig. 10. In comparison to the high forecast error scenario, the absolute amount of imbalances is lower for each day in the low forecast error scenario, due to the smaller magnitude of forecast errors. In addition, a higher amount of imbalance reduction is achieved in low forecast error scenario since the total amount of flexible loads remains the same and the absolute amount of imbalances is reduced. However, despite the lower absolute amount of imbalances, not all the imbalances can be resolved even in the low forecast error scenario. One reason for this is the time limitation on load shifting: the flexible loads can only be shifted 8 PTUs before or after the original timing of consumption. Another reason is the type of forecast

error. For example, on June 11th, the reduction in the total amount of imbalances is still equal to 0% as it is a single-direction error day.

5.4. The impact of types of consumers

The difference between the residential and service sector is noticeable in Fig. 10. Especially on June 8th, the reduction in the service sector is greater than the residential sector. This can be explained by the differences in the demand profiles of the residential and the service sectors. Residential consumption peaks in the early morning and evening hours, while service sector consumption primarily occurs during the daytime hours, coinciding with the highest absolute imbalances. In addition, although the imbalance reductions are approximately the same for the residential and service sector as given in Fig. 7, the service sector has relatively fewer flexible loads. Thus, the utilization of the flexible loads for internal balancing is higher in the service sector compared to the residential sector, also as a result of the demand profiles in the service sector.

5.5. Aggregator’s imbalance costs

Based on the schedule for the flexible loads, the positive and negative imbalances, the imbalance cost for the aggregator for each day in June is computed and depicted for the residential sector in Fig. 11 when DR for internal balancing is applied and when it is not applied. Negative cost values signify a profit to the aggregator. This figure shows that the

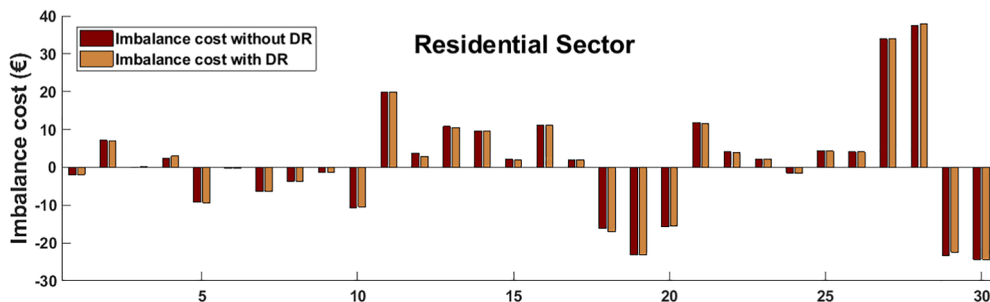


Fig. 11. Imbalance costs for the aggregator with DR for internal balancing and without DR, for every day in June in the residential sector. Negative cost values signify a profit.

cost values do not decrease when DR for internal balancing is applied. The same also applies for the service sector. For this reason, even though the total amount of imbalances is reduced using the MPC model, the imbalance costs for the aggregator remain nearly identical. However, this can be anticipated from the formulation of the MPC. The objective, in the MPC model, is not to minimize the aggregator's costs, but to minimize the individual imbalances of the aggregator. As both the positive and negative imbalances are to be minimized, the revenue that might come from the positive imbalances and the cost that might be generated by the negative imbalances are not optimized. The consequence of not having financial incentives is addressed in the discussion section.

## 6. Discussion

An MPC model is formulated to reduce the aggregator's individual imbalances and applied to a case study in the Netherlands. The results show that DR for internal balancing using the MPC model is successful in reducing the aggregator's individual imbalances. However, it should be stressed that the results are heavily dependent on solar generation forecasts: the types of forecast errors and the magnitude of forecast errors. Moreover, the results provide insight about the lack of financial incentives for the aggregator.

*Type of forecast errors.* The reduction in the total amount of imbalances can be attained only on the switching error days. In line with this, on single-direction error days, the imbalances cannot be decreased. Hence, the ability of DR for internal balancing to reduce the total amount of imbalances is limited by solar generation forecasts. This result links the potential of DR to weather forecasts. To the best of our knowledge, relating weather forecasts to DR potential has not been studied in the existing literature. Moreover, this result also shows that availability of weather forecast data is required to improve the understanding of interactions between weather forecasts and DR.

*Magnitude of forecast errors.* The results from the low forecast error scenario indicate that as the magnitude of solar generation forecast errors decreases, DR for internal balancing is able to reduce more imbalances. The advancements in solar forecasting techniques enable to forecast solar generation with better accuracy [37]. The influence of aggregation of solar generation on the solar generation forecast errors is studied in the literature and it is found that the errors drop as the aggregated solar generation capacity increases [38]. In these cases, DR for internal balancing is expected to become more efficient in reducing the aggregator's individual imbalances.

Nonetheless, even in the low forecast error scenario, some imbalances cannot be resolved due to the type of the forecast error or the time limitation on load shifting. The flexible loads are assumed to be only shiftable within a time frame of 8 PTUs of original timing of consumption, based on [21], to take the consumers' comfort into consideration.

Lastly, the total amount of imbalances and the imbalance costs are calculated using the last updated solar generation forecasts. However, in real-life, the last updated forecast which is received by the aggregator shortly before the beginning of every hour might differ from the actual solar generation. In this case, the aggregator has to deal with different imbalance and imbalance costs. In this paper, the last updated forecast is assumed to correspond to actual solar generation due to high accuracy of 1 h ahead solar generation forecasts [39].

*Incentives.* The results also indicate that even though DR for internal balancing succeeds in reducing the aggregator's individual imbalances, the aggregator's imbalance costs do not decline and stay nearly the same. This is in line with the findings from another paper [19] that studies CHPs to minimize imbalances. From the TSO's perspective, DR for internal balancing is considered useful for the power system in terms of reducing the aggregator's individual imbalances. However, from the aggregator's perspective, DR for internal balancing is not profitable. As a result, the aggregator is not incentivized to use DR for internal

balancing.

The results and the MPC model reported in this paper can be valuable for both aggregators and TSOs. It can also be concluded from the results that TSOs should provide incentives in order to motivate aggregators and other market participants to apply DR for internal balancing. TSOs can use these results to apply relevant incentive mechanisms to financially motivate aggregators to use DR for internal balancing. With the appropriate incentives, aggregators might become financially interested in applying these results and the MPC model, and thus to reduce their individual imbalances. This analysis is based on historic imbalance prices which arise from a power system dominated by conventional power plants. The questions remain on how the imbalance prices will change in the future with higher penetration of RES in the power system and how these changes will influence this analysis.

*Number of consumers in the portfolio.* If the number of consumers in the aggregator's portfolio increases, internal balancing is expected to perform better as (1) the available number of flexible loads for DR becomes greater and (2) the increase in the aggregated solar generation capacity enables more accurate forecasting.

This paper focuses on the use of DR to reduce the individual imbalances of an aggregator. To be able to implement DR successfully, other aspects of DR should also be considered, such as regulatory barriers, market design, and incentives. A comprehensive review of financial incentives to motivate the consumers to participate in DR is provided in [40]. Furthermore, the main regulatory and market barriers that hamper the successful development of DR are identified in [41].

## 7. Conclusion

The aim of this paper is to evaluate the impact of demand response for internal balancing to reduce the individual imbalances of an aggregator, caused by uncertain solar generation. Demand response from flexible loads in both residential and service sectors are considered. A comprehensive Model Predictive Control model is presented to reduce the aggregator's individual imbalances. This model is applied to a case study in the Netherlands.

The results show that demand response for internal balancing using Model Predictive Control model is successful in reducing the aggregator's individual imbalances up to 30% in June. However, these results are heavily dependent on solar generation forecasts: the type of forecast errors and the magnitude of forecast errors. The imbalances can only be reduced on so-called switching error days. Also, more imbalances can be resolved with lower magnitude forecast errors. The aggregator's imbalance costs remain almost identical with demand response for internal balancing. In a broader perspective, a reduction of the aggregator's individual imbalances is beneficial for the power system. Notwithstanding, from the aggregator's point of view, it does not provide any financial benefits for aggregator to reduce their individual imbalances. The results presented in this paper may provide a base to explore incentives to stimulate an active role of aggregators in using demand response for minimizing individual imbalances.

In this paper, the consumers' viewpoint is not studied. More specifically, the contracts between the aggregator and the residential and service sector consumers, and the price the aggregator should pay to consumers to be able to implement demand response, is not taken into consideration. This can be a subject for further research. Also, future work can incorporate the difference between the last updated solar generation forecast and actual solar generation.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.apenergy.2019.04.035>.

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