# Utilizing the flexibility of distributed thermal storage in solar power forecast error cost minimization

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## Abstract

Intermittent renewable energy generation, which is determined by weather conditions, is increasing in power markets. The efficient integration of these energy sources calls for flexible participants in smart power grids. It has been acknowledged that a large, underutilized, flexible resource lies on the consumer side of electricity generation. Despite the recently increasing interest in demand flexibility, there is a gap in the literature concerning the incentives for consumers to offer their flexible energy to power markets. In this paper, we examine a virtual power plant concept, which simultaneously optimizes the response of controllable electric hot water heaters to solar power forecast error imbalances. Uncertainty is included in the optimization in terms of solar power day-ahead forecast errors and balancing power market conditions. We show that including solar power imbalance minimization in the target function changes the optimal hot water heating profile such that more electricity is used during the daytime. The virtual power plant operation decreases solar power imbalances by 5 – 10 % and benefits the participating households by 4.0 - 7.5 € in extra savings annually. The results of this study indicate that with the number of participating households, while total profits increase, marginal revenues decrease.

## Keywords

Thermal storage; Virtual power plant; Solar; Demand response; Forecast error cost

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## 1. Introduction

The electricity markets are facing radical changes and innovations. The battle against climate change is forcing us to increase the amount of variable and intermittent renewable energy sources (RESs), such as wind and solar, in power systems. The fluctuating nature of intermittent RESs causes additional uncertainty and costs in the operation of the power system. These intermittency costs[2] have been identified, categorized and calculated in many recent studies (Hirth, 2013; Hirth, 2016; Hirth et al., 2015; Gowrisankaran et al., 2017; Huuki et al., 2017). As a result, more attention has been paid to the efficient network control and the provision of balancing services. Fortunately, at the same time, the development of information and communication technology (ICT) has enabled more efficient power system operations. In other words, the power grids are constantly becoming smarter (Wissner, 2011). The traditional unidirectional supply chain from the electricity producers to the consumers through the transmission and distribution grid is becoming a bidirectional supply chain, as consumers can feed their own distributed generation back to the grid.

The development of energy storage technologies can be viewed as an additional enabler of cost-efficient RES integration (a recent review article on energy storage technologies can be found in Koohi-Fagyeh and Rosen (2020)). In other words, the ability to store energy is one means of limiting the costs of integrating wind and solar power by buffering the volatility induced by the RES (Xia et al., 2018). Generally, the storage technologies can be categorized into the following three classes: bulk storage, which operates over timescales of hours to weeks; load shifting storage, which is operated from minutes to hours; and power quality storage, which operates from seconds to minutes (Staffell and Rustomji, 2016). The grid-scale bulk energy storage technologies, such as pumped hydro (Karhinen and Huuki, 2019) and compressed air (Berrada et al., 2016), may already be profitable in markets with a sufficiently high electricity price spread. However, the large-scale deployment of electricity storage is highly sensitive to the investment costs (McPherson et al., 2018).

The growth of the energy storage market is resulting in lower investment costs for non-bulk storage technologies. For example, the goal of increasing the self-consumption of photovoltaic (PV) power has led to batteries being deployed in residential houses (Pena-Bello et al., 2017). Despite this development, the economic viability remains an issue due to the current investment costs. As shown, for example, by Barsali et al. (2017), the profitability of the electrochemical storage can be expected

[2] Also called the integration costs of RES (Hirth, 2013).

to increase in the future as the investment costs continue to decline. Although the increased investment intensity may not always be purely market-based (see, e.g., Kairius et al. (2019) for a discussion of the German case), it seems that the commercial residential storage markets are becoming economically attractive for consumers in the future.

The development of ICT and energy storage has opened possibilities for novel distributed $CO_2$ emissions-free energy solutions in power systems. The new solutions aim to increase the resource use efficiency, which is why they should be efficiently integrated into the power system operations. In other words, while aiming to reduce the $CO_2$ emissions in the electricity sector, the reliability of and security of the electricity supply in the power systems must be ensured. We, among other researchers in this field and also in other technological disruption fields[3], propose that new types of business models and trading mechanisms are needed to activate the potential of the new technological solutions. The operators providing these solutions in the power markets are called aggregators (Campaigne and Oren, 2016), microgrids and virtual power plants (VPPs) (Nosratabadi et al., 2017).

The operation of a VPP depends on the electricity consumption and production resources under its control, which are linked to the questions of economies of scale and scope, as well as to the design of a proper business model. The scale questions involve finding an optimal amount of resources from a certain viewpoint, i.e., either the household's or the VPP operator's perspective. The scope aspect arises from the fact that the VPP may choose to participate in different marketplaces and offer various types of services to its customers. In addition to electricity bill minimization, these services can include, for instance, home automation (Vega et al., 2015) and electric vehicle charging (Nunes et al., 2015). Several business models ranging from nonprofit or profit types to different types of co-operatives can also be applied (Akasiadis and Chalkiadakis, 2017).

The most exciting finding of the VPP literature review in Nosratabadi et al. (2017) is that there are not many studies investigating the demand response in VPPs from the household perspective. Instead, most reviewed studies focus on different technical aspects related to VPPs but not on the cost savings for households from permitting the VPP operator to control their electricity consumption. An exception to this is provided by Richter and Pollitt (2018), who investigate the consumer preferences

[3] The sharing economy, or peer-to-peer markets, provides an alternative to long-established firms in the supply of services and goods. The impact of one of the best known recent multisided platform services, Airbnb, is analysed in Zervas et al. (2017). Other new disrupting initiatives, such as Uber, are discussed in Kenney and Zysman (2016). These are thoroughly analysed by Henten and Windekilde (2016) in Coase's (1973) transaction cost framework. Finally, Martin (2016) suggests that the current pathway of the sharing economy does not necessarily result in a transition to sustainability.

towards VPP pricing strategies with a discrete choice experiment. This gap in the literature leads to the main contributions of this article, which are as follows:

i) we study the economics of scale and quantify the average and marginal added values of the individual households participating in the VPP operation,

ii) we study the economics of scope by using hot water heaters as a thermal storage resource both in the household's heating cost and solar power forecast error cost minimization, and

iii) we show the market value of weather forecast accuracy (see also Martinez-Anido et al., 2016).

The contributions listed above are studied with the developed VPP model, which includes controlling the consumption and production resources in a setting that combines models and elements from the previous VPP, demand response and weather forecasting literature. The flexibility is provided by the individual households whose electricity demand flexibility is used to balance the forecast errors of a PV power plant with a capacity of one[4] megawatt-peak (MWp). The VPP operator seeks to minimize the forecast error costs given the uncertainty[5] related to the balancing power market conditions and solar power forecasts[6]. In other words, the VPP operator may bid its production based on the latest forecast available at the day-ahead market closure and face the consequences of forecast errors in the energy imbalance market after the uncertainties have been realized. Alternatively, the operator may utilize the controllable flexible consumption resources to compensate for the forecast errors internally.

The households are key players providing electricity demand flexibility in future power systems. In the past several years, a large stream of literature examining the different demand response (DR) programmes has been built (for thorough literature reviews see, e.g., Faruqui et al. (2010) and Katz et al. (2016)). These programmes are typically divided into price- and incentive-based programmes (Finn et al., 2011). According to Borenstein et al. (2002), real-time pricing with prices varying hourly can be considered the most prominent and economically efficient way to implement demand

[4] 1 MWp describes the size of a large-scale solar power plant in Finland. For example, 0.9 MWp systems have been installed on the roofs of supermarkets and the electricity generation company Helen has a 0.85 MWp solar plant on the roof of a skiing hall.
[5] Much of the relevant VPP literature discusses the stochastic elements in VPP optimization. In short, the stochasticity in the VPP operations can be related to wind power (Tajeddini et al., 2014; Tascikaraoglu et al., 2014), solar power (Tascikaraoglu et al., 2014; Zamani et al., 2016), load (Dabbagh and Sheikh-El-Eslami, 2015; Zamani et al., 2016) or electricity prices (Dabbagh and Sheikh-El-Eslami, 2015; Tajeddini et al., 2014; Shafie-khan et al., 2013; Zamani et al., 2016). Along the lines of the previous literature, the uncertainty in this study is related to the solar power output and balancing power market conditions.
[6] For instance, wind power forecast errors, defined as the difference between the day-ahead output forecast and the realized output, increase the imbalance power costs (Holttinen et al., 2011; Hirth et al., 2015). The same applies for solar (Hirth, 2015).

responses in power markets. The potential for real-time pricing to increase the efficiency of power system operations was recently shown in Huuki et al. (2017). In this study, it is assumed that the consumers are under real-time pricing.

The technological aspects need to be considered in designing demand response programmes[7]. In other words, there are differences in, for example, whether the control is related to heating or other electricity usage (Ruokamo et al., 2019). Although the household-scale battery systems are already available (e.g., Kairies, 2019), there is other underutilized storage capacity available in the residential buildings. A resource that combines both the energy storage and demand response perspectives is related to the use of a building's thermal mass (Thieblemont et al., 2017; Verbeke and Audenaert, 2018) and household water in electric hot water heaters (EHWH) (Kepplinger et al., 2015; Karhinen et al., 2018).

In this article, we treat EHWHs as controllable distributed thermal storage containers[8]. The EHWHs provide substantial technical flexibility in smoothing out the RES output variation, as they typically have oversized heat-absorption capacities and are well-insulated. Most importantly, their temperature can be adjusted without sacrificing the comfort level (Vanthournout et al., 2012). From an economic perspective, load shifting under a real-time pricing contract from high- to low-priced hours results in heating cost savings[9] (Karhinen et al., 2018). Regarding the existing VPP literature, for example, Thavlov and Bindner (2015) considered the utilization of buildings' thermal mass in a VPP set-up. However, these researchers do not quantify the monetary benefits at a household level, which is the focus in our study.

This paper is organized as follows. In Section 2, we propose a virtual power plant model incorporating the necessary elements to elaborate the contributions listed above. The market framework determines the VPP operator's trading decisions. Therefore, after the model is specified, we apply it to the Finnish power market by investigating a set of different scenarios. The Finnish power market, PV power forecast data and model parameters are introduced in Section 3. The results are presented and discussed in Section 4, and Section 5 concludes the paper.

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[7] Additionally, it is essential to offer properly designed incentives to the end-users to avoid behavioural and economic barriers to activating the demand response potential (Torriti et al., 2010; Hobman et al., 2016).

[8] Different technologies such as conventional pumped hydro energy storage (Karhinen and Huuki, 2019) and more state-of-the-art technologies, such as batteries (Luo et al., 2015), are examples of energy storage solutions that are already usable in VPP applications.

[9] Instead, from the electricity bill perspective, there is nothing to be optimized if the household has a fixed-price contract and total consumption remains fixed.

## 2. Virtual power plant operation with demand response

In this section, we attempt to show how solar power generation forecast errors can be internally balanced by aggregating and utilizing individual households' electric hot water heaters. The model formalization is started by examining the generation and consumption resources separately in Section 2.1. First, the computation of the imbalance costs/revenues arising from the errors between the actual and day-ahead forecasted solar power outputs is shown in Section 2.1.1. Second, in Section 2.1.2, the hot water heating costs of a representative household are minimized based on hourly varying day-ahead market prices[10]. The forecast errors for solar power generation and water heating under the control of a VPP operator are considered together in Section 2.2.

The model framework is presented in Figure 1. In the benchmark setting, the solar power producer passively sells and buys imbalance power (surplus or deficit) to compensate for its forecasting errors, and households buy electricity from the grid to heat water. In the VPP setting, the problem becomes dynamic, as represented by the dotted lines in Figure 1, when both resources are controlled by the VPP operator. In summary, if the solar power realization is higher than forecasted (surplus), the VPP operator may use some or all the surplus output for water heating and sell the residual surplus to the Transmission System Operator (TSO) at the imbalance power market price. Alternatively, the VPP operator may direct some of the contracted electricity from the grid to counterbalance the deficit solar power output in case the realization is lower than forecasted (deficit).

[10] Day-ahead prices are also called real-time prices in, e.g., Kopsakangas-Savolainen and Svento (2012).

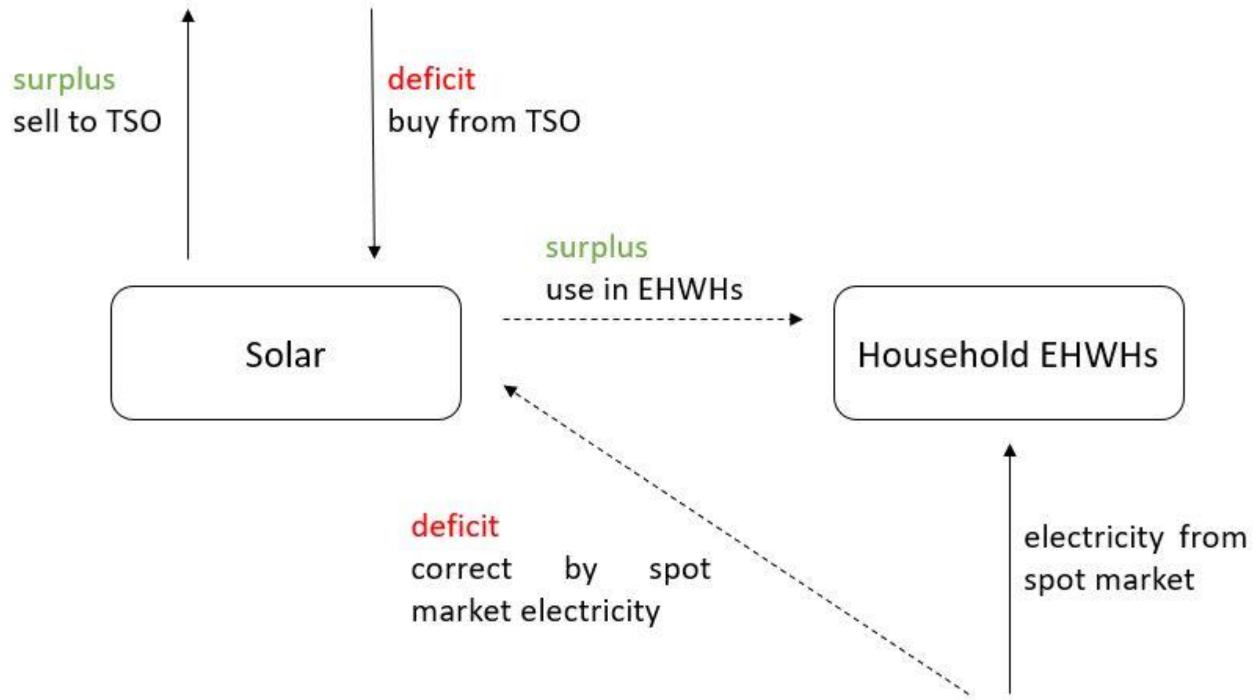


**Figure 1. Virtual power plant balances any imbalances caused by the day-ahead solar power forecast errors by operating with the TSO or by controlling the consumption and generation units. The dotted lines represent the additional layer of the VPP operator optimization.**

## 2.1. Resources without coordination by the virtual power plant operator

### 2.1.1. Solar power producer's imbalance

In this section, we provide a simplified description of a conventional imbalance power management method that is applicable for various markets with some modifications. Typically, each market participant must ensure its own power balance. In other words, the difference between its electricity production/procurement and consumption/sales must be balanced with imbalance power. In practice, these balances are maintained with the help of a compulsory open supplier. As described in Chaves-Ávila et al. (2014), Balance Responsible Parties (BRPs) take care of the open suppliers' power balances and trade imbalance power with the TSO. In this paper, it is assumed that the power balance of the solar power producer is maintained by a specific BRP, who allocates all the costs associated with the solar power producer's generation imbalances directly to the producer. We assume that the solar producer's generation capacity is sufficiently small (1 MWp) that it does not have any significant effects on balancing the power market equilibrium quantity and price, despite the possible forecasting errors. In other words, the balancing market reactions are not endogenized in our calculations.

Any producer is obliged to submit a production plan for the balance market in case it has sufficiently large generation units. The initial production plans are submitted to the TSO the day before delivery. Subsequently, the initial production plans are updated constantly such that any expected imbalances can be included in the TSO's balancing plans. In this descriptive case, a two-price imbalance system[11] with different prices for the purchasing and selling of imbalance power is used (for the differences in one-price and two-price systems, refer to, e.g., eSett (2018)).

The TSO sells and buys imbalance power to and from the BRPs. In case of a deficit production balance, the producer needs to buy imbalance power via the BRP from the TSO. The purchase price of imbalance power for the BRP is the hour-specific up-regulation price ($p_t^{up}$) in the balancing power market. The purchase price is equal to the day-ahead market (DAM) price ($p_t^{dam}$) in that hour in case there is no up-regulation, or the hour is defined as a down-regulation hour. Conversely, in case of a surplus production balance, the TSO buys imbalance power from the BRP at the down-regulation price ($p_t^{down}$) in that hour. If there is no down-regulation or the hour is defined as an up-regulation hour, the purchase price is equal to the day-ahead market price defined for that hour. Table 1 summarizes the imbalance revenue in two-price system. The power imbalance $e_t$ is marked as the power sold to the day-ahead market less the realized production.

*Table 1. Imbalance revenue in a two-price system.*

| | **Up-regulation** | **No regulation** | **Down-regulation** |
|---|---|---|---|
| **Excess ($e_t < 0$)** | $-e_t p^{dam}$ | $-e_t p_t^{dam}$ | $-e_t p_t^{down}$ |
| **Deficit ($e_t > 0$)** | $e_t(p_t^{dam} - p_t^{up})$ | $e_t(p_t^{dam} - p_t^{dam}) = 0$ | $e_t(p_t^{dam} - p_t^{dam}) = 0$ |

Considering our case study, which is described in more detail in Section 3, a solar power producer forecasts its generation on a day-ahead basis for each hour the next day. Forecast error costs arise from not being able to bid correctly in the day-ahead market and paying for any imbalances in the

[11] In contrast, a single-price system with equal purchase prices can be used on the consumption side. In up-regulation (down-regulation), the hour imbalance power price is the up-regulation (down-regulation) price. The imbalance price is equal to the day-ahead market price if no regulation is made. According to the typical market rules, a producer does not have to submit a production plan to the TSO if all its individual generator resources are smaller than 1 MW. As an example, according to the Finnish TSO Fingrid's balance service rules, the production of a smaller generation unit is still allowed to be handled in the production balance. In this case, the production is treated in the consumption balance as a small-scale production. In other words, the small-scale production is deducted from the consumption.

imbalance power market. The hourly forecast error is marked as the difference between the estimated day-ahead production ($solar_t^{dam}$) and the realized solar power production ($solar_t^{real}$). At hour $t$ of delivery, the forecast error $e_t = solar_t^{dam} - solar_t^{real}$ may be one of the following:

- The solar power generation is perfectly forecasted in the day-ahead market, i.e., $e_t = 0$.
- The day-ahead forecasted solar power generation is lower than the realized solar power generation (surplus: $e_t < 0$)
    - If the system is in a down-regulation state, the solar power producer receives the down-regulation price $p_t^{down} < p_t^{dam}$ for the surplus generation $e_t$. If the solar power had been perfectly forecasted, production $e_t$ could have been sold at the day-ahead market price $p_t^{dam}$. Consequently, the forecast error cost (see Table 2) is $e_t(p_t^{dam} - p_t^{down})$.
    - The TSO's imbalance power purchase price is $p_t^{dam}$ in case of an up- or no-regulation system state. The forecast error cost for excess generation in these cases is zero.
- The day-ahead forecasted solar power generation is higher than the realized solar power generation (deficit: $e_t > 0$)
    - If the system is in an up-regulation state, the solar power producer pays the up-regulation price $p_t^{up} > p_t^{dam}$ for the required imbalance power $e_t$. If the solar power had been perfectly forecasted, production $e_t$ would not have been sold at the day-ahead market price $p_t^{dam}$ in the first place. Consequently, the forecast error cost is $e_t(p_t^{dam} - p_t^{up})$.
    - The TSO's imbalance power selling price is $p_t^{dam}$ in case of a down- and a no-regulation system state. The forecast error cost for a deficit generation in these cases is zero.

Table 2 summarizes the forecast error cost calculation in a two-price imbalance system. In this paper, it is assumed that the VPP operator cannot improve the forecasts as such. Instead, the VPP operator can minimize the forecast error cost by maximizing the imbalance revenue by optimizing the allocation of the solar power forecast error between the imbalance power market and the controllable consumption resources.

*Table 2. Forecast error cost in the two-price system.*

| | Up-regulation | No-regulation | Down-regulation |
|---|---|---|---|
| **Excess ($e_t < 0$)** | 0 | 0 | $e_t(p_t^{dam} - p_t^{down})$ |
| **Deficit ($e_t > 0$)** | $e_t(p_t^{dam} - p_t^{up})$ | 0 | 0 |

*Note:* error $e_t = solar_t^{dam} - solar_t^{real}$.

### 2.1.2. Household water heating optimization

As a starting point in storage optimization, we examine the water heating costs of a representative household, who optimizes its heating with respect to hourly electricity price signals and a set of consumption and technical restrictions. The optimal policy minimizes the electricity cost related to water heating as follows:

$$\sum_{t=1}^{T} \beta^{t-1} x_t p_t^{dam}, \tag{1}$$

subject to the energy content transition equation and storage limits, as follows:

$$0 \leq S_{t+1} = S_t - c_t - L(S_t) + x_t \leq \bar{S}, \tag{2}$$

and the heating power limits, as follows:

$$0 \leq x_t \leq \bar{x} \quad \text{for all } t, \tag{3}$$

where $t$ denotes the hour, $T$ is the number of hours in a year, $\beta$ is the discount factor, $x_t$ is the electricity used for water heating (kWh), $p_t^{dam}$ is the electricity price in the day-ahead market (cent/kWh), $S_t$ is the energy content (kWh) in the heater, $c_t$ is the hot water consumption in energy units (kWh), $\bar{S}$ (kWh) is the maximum energy content of the heater, and $\bar{x}$ is the hourly maximum heating energy of the heater (kWh). The heat loss is a function of the amount of energy stored in the water $L(S_t)$. It is assumed that heated water flows up in the heater[12]. Heat loss takes place on the

[12] A thermal model assuming perfect mixing inside the EHWH is used, e.g., in Kapsalis and Hadellis (2017) and Kepplinger et al. (2015).

surface area where the temperature is higher than the household's indoor temperature. The heat loss function is written as follows:

$$L(S_t) = \left(UA \cdot \frac{S_t}{\bar{S}} \cdot \Delta T_{env}\right) \cdot 10^{-3}, \tag{4}$$

where $UA$ is the thermal conductance and $(S_t/\bar{S})$ is the share of the surface area related to the heat loss from the heater. The temperature difference between the heated water and the ambient indoor air is denoted by $\Delta T_{env}$.

The model is solved as a discrete-time dynamic optimization problem where the energy content $S_t$ is the state variable and electricity for heating $x_t$ is the policy variable, as follows:

$$V_t(S_t) = \min_{x_t}\{x_t p_t^{dam} + \beta V_{t+1}(S_{t+1})\}, \tag{5}$$

subject to the transition Equation (2) as well as the energy and hot water heater power constraints in Equations (2) and (3), respectively. The energy content in the first period $S_1$ is given, and $S_{T+1} = S_1$ is reached by setting a fine for the maximum hourly price for the energy content at the hour $(T + 1)$ below $S_1$.

### 2.2. Coordination of virtual power plant operations with solar power and demand response resources

The virtual power plant has household electric hot water heaters to balance the solar power forecast error. Assume now that $N$ households have become customers of the VPP. These customers have granted the VPP the right to decide when to heat the water in the EHWHs in these houses, given that hot water is available when needed. The VPP operator must now solve its optimal operation by taking the following into account: i) the optimal amount of electricity from the grid used for water heating, ii) the allocation of excess solar power generation to water heating and iii) the amount of electricity bought from the grid to balance the solar power generation deficit. The target of the VPP operator is defined as maximizing the solar power generation imbalance revenue (Section 2.1.1) less the hot water heating costs (Section 2.1.2).

In hours when the sun is below the horizon, there is no uncertainty in the optimization, as no solar power forecasting errors can occur. Conversely, the uncertainty is related to solar power forecast errors and balancing the market outcome in the hours when the sun is above the horizon. The optimization decision is made in two phases in the hours that involve uncertainty. First, the forecast error realization occurs in hour *t*. This is because the VPP knows the amount of solar power sold in the day-ahead market and can monitor the actual solar power production within the delivery hour. Second, the system balance direction and imbalance price are realized after hour *t*. This is because the balancing energy prices are published after the delivery hour (Fingrid, 2018).

The VPP's control variables ($x_t$ and $e_t^{vpp}$) and events ($e_t$,$IB_t$ and $p_t^{im}$) have the following timing (see Figure 2 for illustration):

1) Given the energy content of the heater ($S_t$), the VPP makes the water heating ($x_t$) decision before hour *t* starts,
2) in hour $t$, the solar forecast error ($e_t$) is realized. Given the error realization, the VPP operator decides the allocation of the forecast error between internal balancing ($e_t^{vpp}$) and the imbalance market operation ($e_t - e_t^{vpp}$),
3) The system balance direction ($IB_t$) and imbalance price ($p_t^{im}$) are realized after the end of hour *t*. These realizations together with the imbalance power ($e_t - e_t^{vpp}$) determine the imbalance market revenue. The next period energy content ($S_{t+1}$) is known, and steps 1 – 3 are repeated for hour $t+1$.

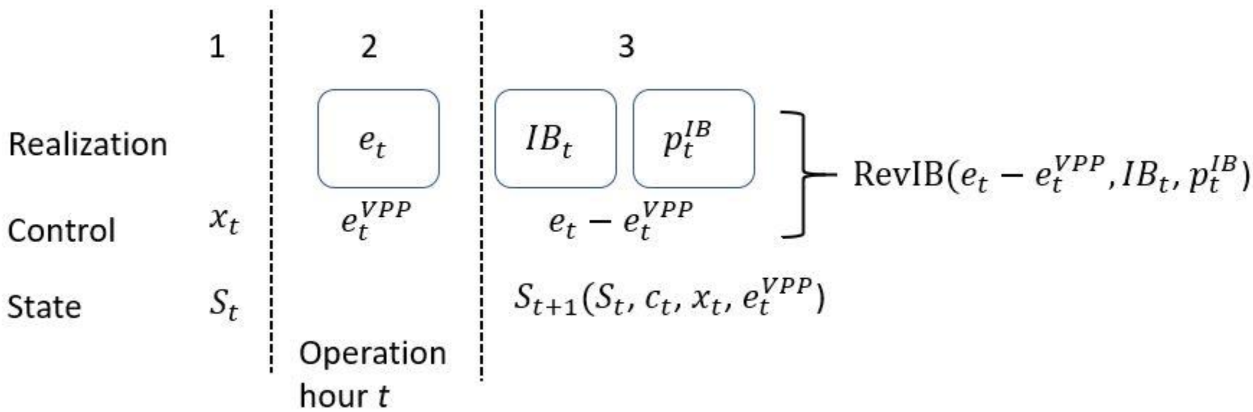


**Figure 2. Coordinated VPP operation before (1), within (2) and after (3) the operation hour. The stochastic components are presented in the frames.**

The coordinated virtual power plant operations with solar power and demand response are presented in detail in Appendix A.

## 3. Description of the Finnish power market, model data and parameters

### 3.1. Reserve and balancing power scheduling

The described model is applied to the Finnish power market, which is a part of the Nord Pool Spot market area. In this market, most of the electricity is traded in a day-ahead auction market where producers and consumers place their bid for hours in the next day. The market is closed at 09:00 AM (Coordinated Universal Time, UTC) on the day before delivery. Bids are made for hours +17…+40. Assuming rational market participants, the bids in this market are made based on the expected market outcome including, for example, the latest production and consumption forecasts. The power balance[13] is maintained in several markets, such as the intraday market, various reserve markets and balancing markets after the day-ahead market is closed. Three situations can occur during the delivery hour. First, the market could be in balance, meaning that the demand and supply were perfectly forecasted in the day-ahead market. Second, there might be excess demand so that more production is needed, or consumption must be reduced. Third, in case of excess supply, the production needs to be decreased or consumption needs to increase.

The TSO utilizes the reserve and balancing power markets to maintain the power balance. The reserve capacity is acquired from the reserve markets closing at 2:30 PM (UTC) the day-ahead of delivery and is used as the primary source of balancing power. In case there are not enough spinning reserves, more capacity is acquired from the balancing power market, which is a voluntary spot market with a marginal-price auction that opens the day before delivery and closes 45 minutes before the delivery hour. In other words, the bids are sorted in an ascending order and the bids with lower prices are activated first. The last activated bid determines the market clearing price that is paid for all activated bids. The market participants can offer both up- and down-regulation bids, which specify the offered volume, price and hour of delivery. The net sum of all activated bids within an hour determines the state of the market[14], i.e., whether the hour is defined as an up- or down-regulation hour[15]. The

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[13] The power balance requirement states that demand must always be equal to supply in the power grid. In technical terms, this translates to maintaining the frequency in the grid within tolerable limits to ensure a high quality supply of electricity.
[14] The BRPs inform the TSO about their production plans 45 minutes before the beginning of the delivery hour. The balancing market state is determined based on the net sum of the BRPs' imbalances.
[15] In case both up- and down-regulation bids are activated within the same delivery hour, the overall state of the market determines the paid price. More specifically, the bids corresponding to the state of the market receive the marginal price, whereas bids that are opposite to the market state receive a pay-as-bid price. We simplify the balancing power pricing such that the balancing power is priced with a marginal price principle.

resources offered to the balancing market are activated in real-time within the delivery hour. The balancing market state and price determine the imbalance market prices described in Section 2.1.1.

The day-ahead market prices as well as the balancing power prices and quantities in the Finnish power system in 2016 are shown in Table 3. As seen, the mean up-regulation price is above the day-ahead market price, whereas the opposite applies for the mean down-regulation price. The up-regulation price is far more volatile than the down-regulation price, with the standard deviation being 3.5 times higher. The price cap of 3000 €/MWh occurred once during the sample period. The moments of the balancing power quantity distributions are more similar than those in the case of the price distributions. It must be noted that the maximum for up-regulation and the minimum for down-regulation are substantial, as they correspond to 3.9% and 2.9% of the load (11 528 MWh and 11 403 MWh, respectively) in the corresponding hours.

*Table 3. Day-ahead and balancing power market descriptive statistics*

| | **Minimum** | **Maximum** | **Mean** | **St. dev.** |
|---|---|---|---|---|
| **Day-ahead market price (€/MWh)** | 4.02 | 214.25 | 32.45 | 13.14 |
| **Up-regulation price (€/MWh)** | 4.04 | 3000.00 | 36.87 | 41.42 |
| **Down-regulation price (€/MWh)** | –25.55 | 200.09 | 28.18 | 11.79 |
| **Up-regulation – Day-ahead market price (€/MWh)** | 0.00 | 2957.25 | 18.72 | 78.69 |
| **Down-regulation – Day-ahead market price (€/MWh)** | 0.00 | 185.25 | 11.06 | 12.39 |
| **Up-regulation quantity (MWh)** | 0.00 | 444.67 | 13.15 | 36.50 |
| **Down-regulation quantity (MWh)** | –330.00 | 0.00 | –19.80 | 40.24 |

The correlation between the load and the up-regulation quantity is 0.262 and the correlation between the load and down-regulation quantity is –0.206. Both correlations are statistically significant at the 1% significance level and they have the expected signs, i.e., a higher load causes higher regulation quantities in both the up-direction and the down-direction. The demanded balancing power quantity affects the price difference between the day-ahead and balancing market prices. The balancing quantities are fully inelastic since the system operator needs to maintain a power balance at all times, even if balancing the power price would be high[16]. The statistically significant (1%) correlations between the price differences and balancing quantities are 0.316 and –0.267 for the up-regulation and

[16] The values of lost load estimates differ between the residential, industrial and service sectors and range from a few €/kWh to more than 250 €/kWh (Schröder and Kuckshinrichs, 2015).

down-regulation states, respectively. This finding implies that the larger the up- (down-) regulation quantity is, the higher (lower) the regulation price is.

The seasonal patterns in balancing prices are shown in Figure 3[17]. As most of the balancing power is supplied with hydro power in Finland, the highest up-regulation prices occur in the spring with the highest inflow to water reservoirs. In other words, during this time, hydro power plants cannot be adjusted as flexibly since the reservoir capacity is limited. Therefore, other more expensive balancing resources must be used more than in other periods. Additionally, the price volatility tends to be higher during the coldest months, with the highest load occurring in the winter. Diurnally, the balancing prices tend to be higher during the day when the load is higher, as shown by the bottom subfigures.

[17] For clarity, up-regulation prices above 200 €/MWh (N = 14) are excluded from the figure.

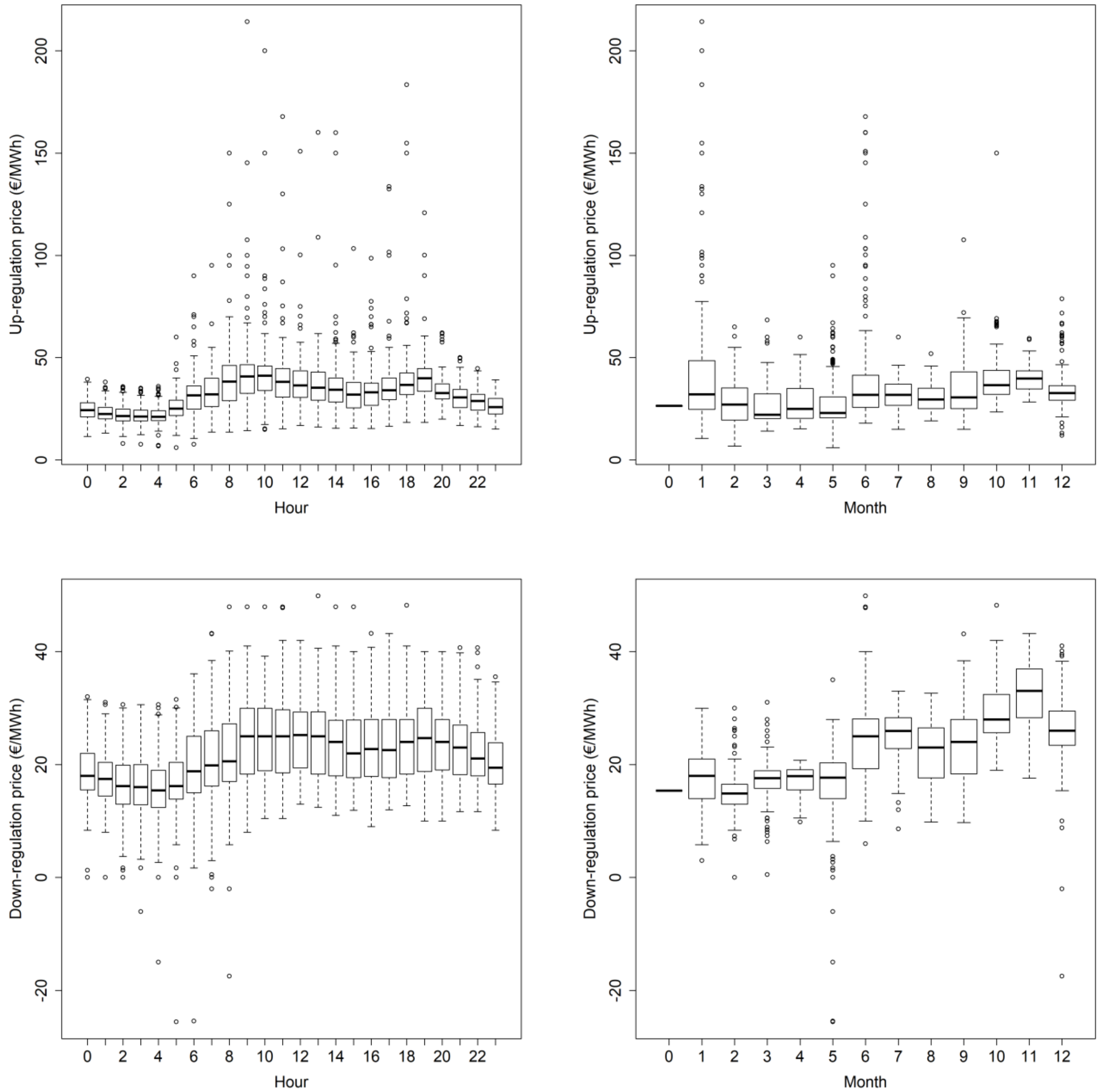


**Figure 3. Seasonal and diurnal patterns of the balancing prices in Finland in 2016.**

## 3.2. Solar power forecasts and the related uncertainty

The actual solar photovoltaic (PV) production data for a system with a nominal capacity of 1 MWp are not available. Instead, we utilize measured production data of a 21 kWp PV system on the rooftop of the Finnish Meteorological Institute in Helsinki, Finland. The nominal capacity of the system is scaled to 1 MWp and the production forecast errors are scaled accordingly. The specifications for the actual solar power site are shown in Table 3.

*Table 3. Specification of the solar power system.*

| | |
|---|---|
| **Latitude** | 60.203561 |
| **Longitude** | 24.961179 |
| **Panel system** | 84 PV Panels, 250 Wp each, 21 kWp in total |
| **Technology** | Poly-Si |
| **Integration level** | Semi-integrated |
| **Slope** | 15 degrees from horizontal |
| **Orientation** | Southeast (135 degrees) |

The PV production forecast is based on the output of the HARMONIE NWP model (Bengtsson et al., 2017). HARMONIE is a physical model that describes the interaction processes related to the state of the atmosphere and produces a numerical forecast of the prevailing weather conditions as an output. This output includes all the relevant parameters needed for obtaining a realistic estimate of the electricity production of a PV system, as described in more detail below and in, e.g., Krishnamurthy et al. (2018).

The hourly time series used in this study consists of consecutive NWP forecasts, which are initialized daily at 06 UTC. The forecast horizon for each of these forecasts is from +17 to +40 hours, i.e., from 23 UTC the same day to 22 UTC the next day. The dataset can thereby be considered a next day forecast.

Table 5 shows the minimum, maximum and standard deviations of the hourly forecasting errors by months. The maximum hourly errors during the snow-free period are approximately 60% of the nominal capacity for both directions. However, the monthly distributions seem to be relatively long-tailed, as the standard deviations of the hourly errors vary between 10% and 14% of the nominal capacity. The sum of the deficit hourly imbalances was 178.1 MWh and the sum of the surplus hourly imbalances was 123.4 MWh in 2016. Consequently, the cumulative solar power imbalance at the end of the annual period is a deficit of 54.7 MWh.

*Table 5. Minimum, maximum, and standard deviation of the hourly errors by month in 2016. Normalized by Wp.*

| Hourly error [W/Wp] | | | |
|---|---|---|---|
| **MONTH** | **MIN** | **MAX** | **SD** |
| **1** | -0.0411 | 0.2456 | 0.0638 |
| **2** | -0.0285 | 0.4962 | 0.0980 |
| **3** | -0.4334 | 0.5273 | 0.1445 |
| **4** | -0.5974 | 0.4390 | 0.1406 |
| **5** | -0.5377 | 0.5857 | 0.1013 |
| **6** | -0.4494 | 0.6232 | 0.1157 |
| **7** | -0.4798 | 0.5318 | 0.1191 |
| **8** | -0.6083 | 0.3886 | 0.1305 |
| **9** | -0.4650 | 0.4236 | 0.1244 |
| **10** | -0.2682 | 0.2858 | 0.0854 |
| **11** | -0.0705 | 0.3091 | 0.0694 |
| **12** | -0.0447 | 0.1426 | 0.0381 |

The presented forecasting model outputs are transformed such that the forecasting uncertainty is incorporated correctly in the optimization model described in Section 2.2. As mentioned previously, there is no solar power uncertainty in those hours when the sun is below the horizon. To illustrate the number of hours where no uncertainty occurs, Figure 4 shows that the sun is up approximately 80 percent of the time in Helsinki in June. In comparison, the sun is up only in 25 percent of the hours in December. Consequently, the level of uncertainty related to VPP optimization varies significantly over the year.

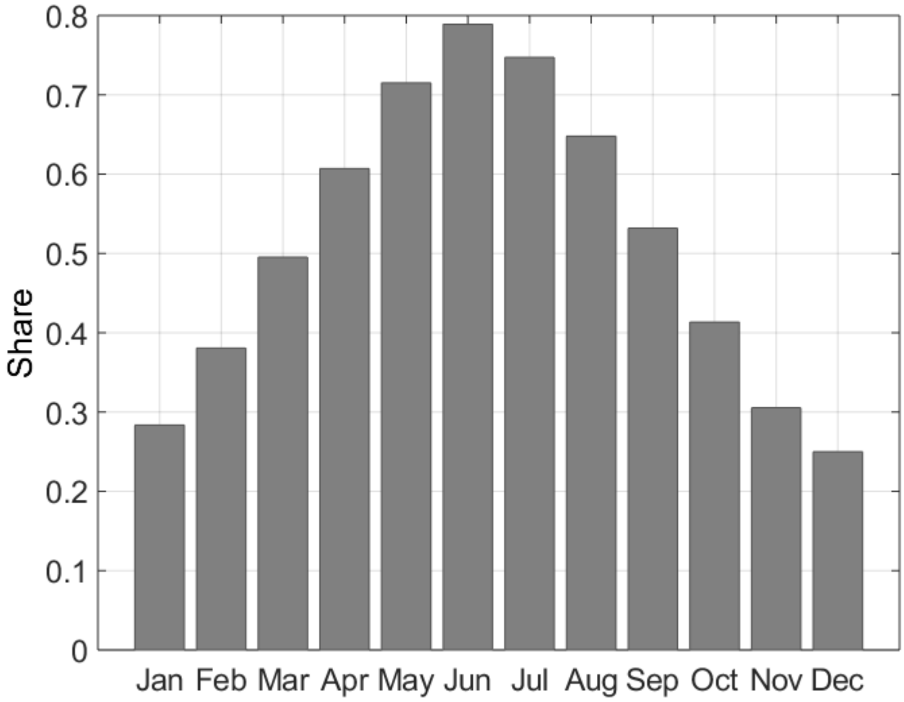


**Figure 4. Share of hours when the sun is above the horizon.**

Each hour-of-day-by-month solar power forecast error distribution is discretized into $L = 10$ points. As an example, the probability distribution functions are illustrated in Figure 5, where the forecast errors (kWh) are on the horizontal axis and the probabilities are on the vertical axis. The greatest uncertainty with respect to forecast errors is during midday, when the sun is the highest above the horizon. The forecast error distribution is narrower in the mornings and in the evenings. As the solar power potential is the greatest during the summer, the distributions are also wider during the summer months. During the winter months, the solar forecast error probability distribution is narrower.

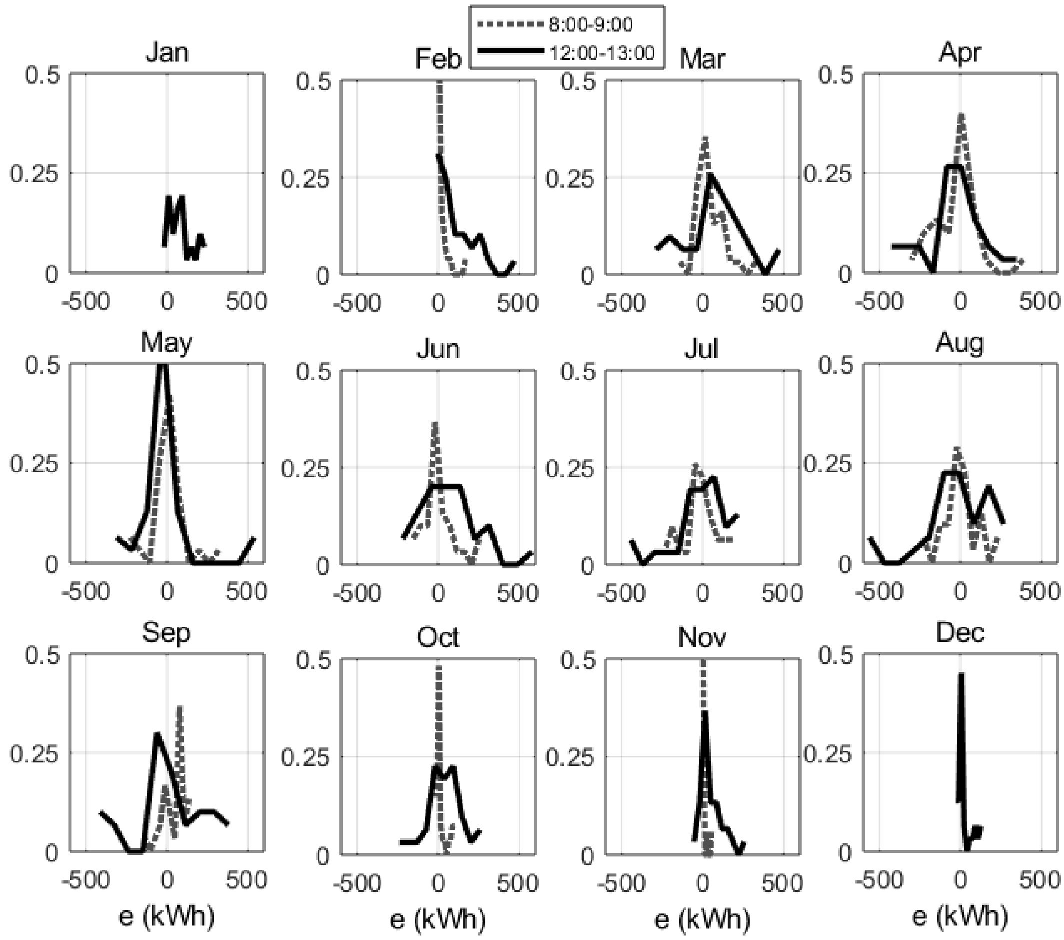


**Figure 5. Solar power forecast error (forecasted – realized) distributions for morning (8:00 local time[18]) and midday (12:00) in each month.**

### 3.3. Model parameters

The household is assumed to have an electric hot water heater with a heating power of 3 kW and a storage volume of 290 litres. The maximum heating energy in an hour is $\bar{x}$ = 3 kWh, and the maximum energy storage capacity is given by the following:

$$\bar{S} = \left(c_p * m * dT\right) * \left(\frac{1}{3600}\right) = 21.15 \text{ kWh}, \tag{6}$$

where the conversion rate from kilojoule (kJ) to kWh is $\left(\frac{1}{3600}\right)$, $c_p = 4.2$ kJ/(kg°C) is the specific heat of water and the mass of water is $m = 290$ kg. The cold inlet water to the heater is set to 5°C and it is heated up to 67.5°C, which results in a temperature change of $dT = 62.5$°C in the heater.

[18] The local time in Finland is UTC+2 during the winter (starting on the last Sunday of October) and UTC+3 during the summer (starting on the last Sunday of March).

The thermal conductance $(UA)$ is set to 1.05 (W/K). With the assumed temperatures, $\Delta T_{env} = 47.5$ K is the temperature difference between the heated water (67.5°C) and the ambient indoor air (20°C). Thus, the theoretical heat loss of a fully heated tank is 50 W, based on the heat loss function in Equation (4). The consumed hot water temperature from the tap is set to 55°C. The representative household, i.e., with two adults and two kids, is assumed to consume 200 litres of hot water per day (Hirvonen et al., 2016). Given the parameters above, the annual electricity consumption used for water heating is 4270 kWh in a representative household.

The total hot water consumption in energy units (kWh) is allocated to different hours with a domestic hot water profile generator DHWcalc by Jordan and Vajen (2017). In brief, we simulate an hourly hot water consumption profile $c_t$. The daily variation of the hot water consumption profile used in the simulations is shown in Figure 6. The dotted line marks the maximum hourly water heating energy potential of the heater, with a heating power of 3 kW. There are several hours when the hot water demand cannot be met by heating the water during that hour. In other words, energy must be stored to fulfil the peak demands.

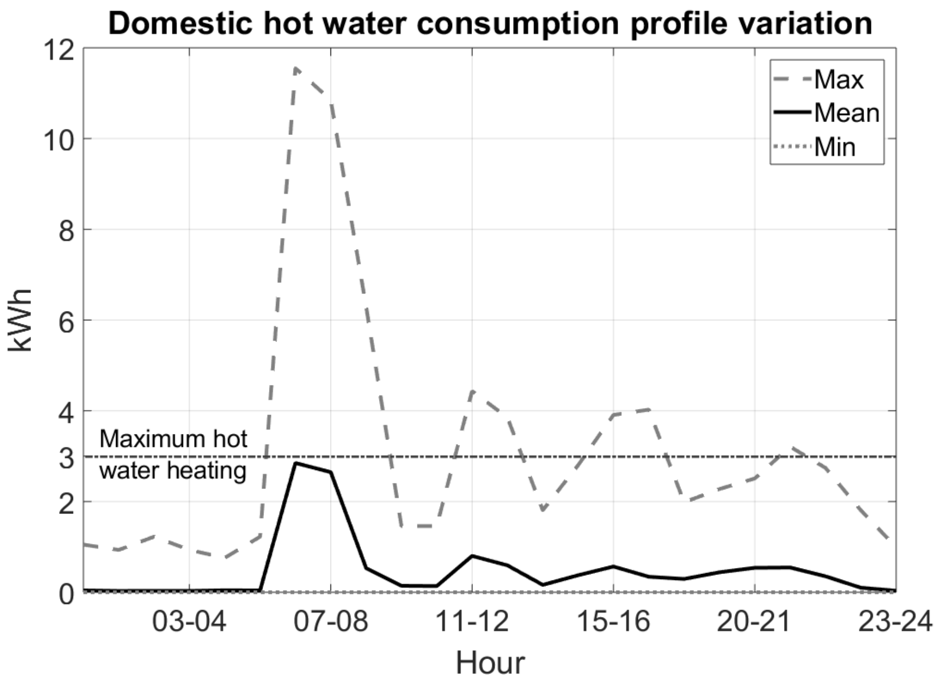


**Figure 6. Domestic hot water consumption profile.**

To simulate the balancing power market outcome, we need to compute the market state probabilities (see Equations 8–9) and formulate the price distributions (see Equations 10–13) based on the data described in Table 3. As shown in Figure 2, the balancing power prices have clear seasonal and diurnal patterns. Therefore, similarly to the solar power forecast error, we define the probabilities and distributions for each hour-of-day-by-month combinations. On average, up-regulation was needed in 22.5% and dow-nregulation was needed in 32.1% of the hours in 2016. Consequently, there was no need for regulation power in 45.4% of the hours in 2016.

The imbalance cost / revenue is determined by the price difference between the up- and downregulation power price and the day-ahead market price in the corresponding hour. Examples of these differences for up- and down-regulation prices are shown in Figure 7 for hours 8 and 22 in January 2016. The distributions are discretized into $M = 10$ points. As indicated by the correlations between the balancing power quantities and prices in Section 3.1, and as shown in Figure 8, both distributions are wider in the hours with higher demand (for example, 8:00-9:00 local time) than in the low demand hours (for example, 22:00-23:00 local time).

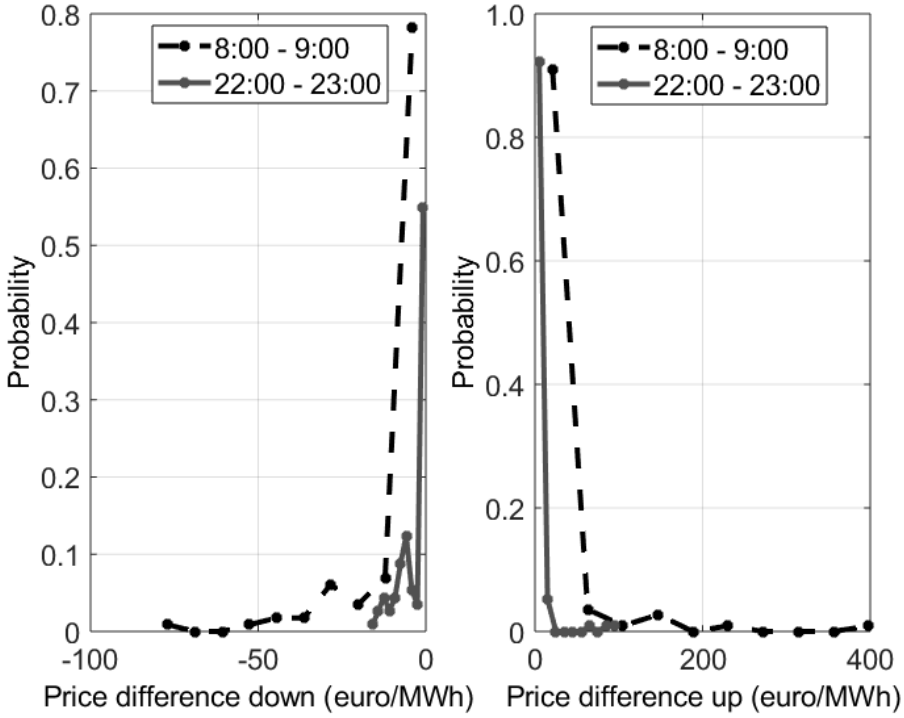


**Figure 7. Probability distributions for up- and down-regulation price differences to the day-ahead market price.**

It is assumed that each household is under a real-time electricity pricing contract, where the price varies hourly based on the power market conditions. The equilibrium prices in this contract are determined by the supply and demand bids in a day-ahead market operated by the Nord Pool. To generalize the model, we abstract from the impacts on the results arising from other electricity cost components[19] in Finland by excluding the taxes and grid fee from the analysis. Finally, the hourly discount rate $\beta$ is set such that the annual discount rate is 3%.

## 4. Results

The simulation results are presented and discussed in this section. The results are the average values over 25 random sample draws from the hourly solar forecast error and imbalance price probability distributions. First, the optimized water heating and solar power forecast errors are simulated as separate resources, i.e., without VPP operation. Section 4.1 shows the costs of optimized water heating of a single household with the model introduced in Section 2.1.2. Additionally, the forecast error cost and imbalance revenue profiles are computed based on the simplified market description in Section 2.1.1. The deterministic VPP optimization results are presented in Section 4.2. Although unrealistic, the perfect foresight operation provides a benchmark to which the results of the stochastic model can be compared. Finally, in Section 4.3, it is shown that the uncertainty faced by the VPP operator reduces the monetary reward allocated to the households and changes the hot water heating profile.

### 4.1. Resources treated separately

The correlation between the optimized hot water heating profile and the electricity price profile is –0.348. A negative correlation implies that the 290-liter water tank provides flexible energy storage capacity with the daily hot water consumption of 200 litres, as it enables load shifting from high-priced to low-priced hours. The annual electricity bill with optimized hot water heating is 99.85€. The average cost of optimized hot water heating energy is 2.34 cent/kWh, whereas the average electricity price is 3.24 cent/kWh.

On average, the annual forecast error cost for the assumed solar power producer is 830 € based on the rules in Table 2, the forecast error distribution presented in Section 3.2 and imbalance price difference distributions presented in Section 3.3. The hourly error costs over the simulations are shown in Figure 8. The majority of costs are accumulated between April and October when the solar output is the highest.

[19] In addition to the hourly varying day-ahead market price $p_t^{DAM}$, the household's electricity bill includes a fixed transmission and distribution (T&D) fee $p^{T\&D}$ (cent/kWh) and a fixed electricity tax $t^E$ (cent/kWh). Additionally, all costs are subject to a value-added tax $t^{VAT}$ (24%).

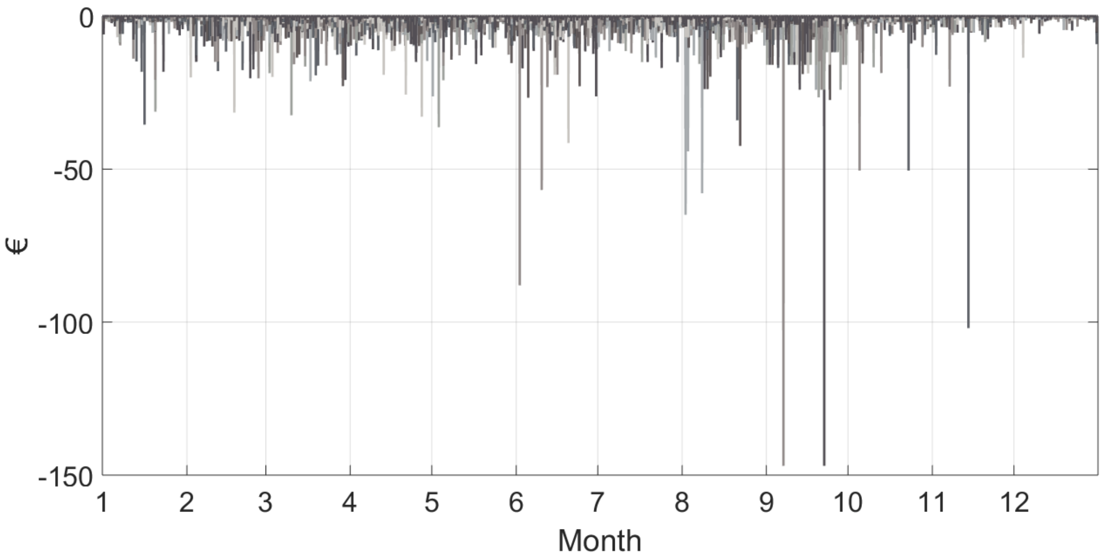


**Figure 8. Solar forecast error cost.**

The hourly imbalance revenue profiles for the simulations are shown in Figure 9. Most of the revenue stream is positive, as the solar power producer can sell the excess electricity at either the day-ahead market price or at down-regulation price (see Table 1). The negative imbalance revenue is related to the hours with an imbalance deficit and an up-regulation market state[20]. Now, according to the rules in Table 1, the average annual solar power imbalance revenue is 3627€.

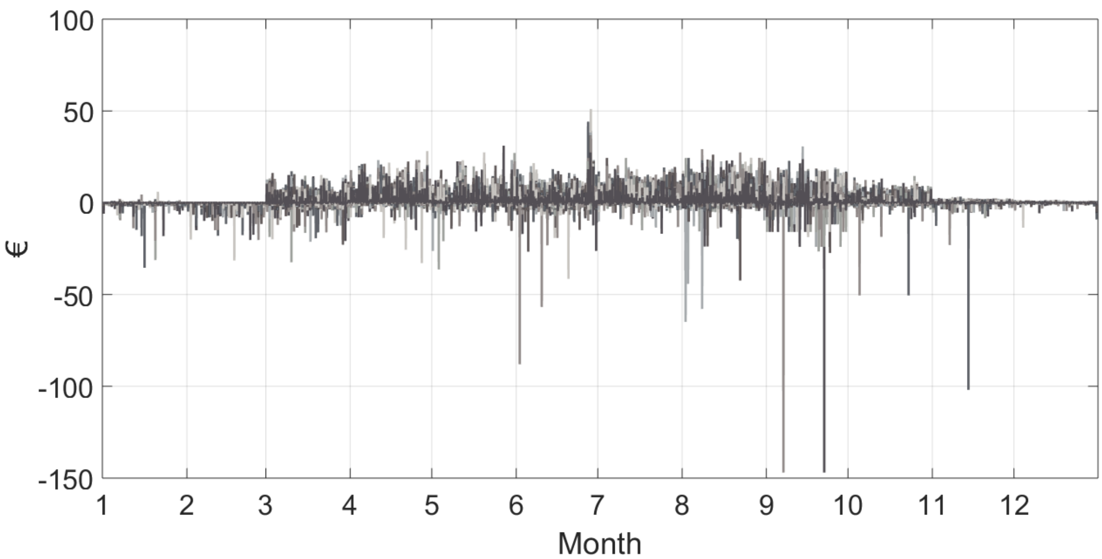


**Figure 9. Solar imbalance revenue.**

[20] The revenue for excess electricity may also be negative if the down-regulation price is negative.

At this point, it must be noted that the annual forecast error cost (830€) is the annual revenue for the excess electricity sold at the day-ahead market price (4457€) less the revenue for the excess and deficit electricity sold at the imbalance price (3627€). Thus, the annual revenues could be increased by 830 € without any forecast errors. In other words, it is the added value of a perfect solar forecast compared to the actual forecast. To give the value a context, it corresponds to 2.5% of the solar power plant's total revenue (32647 €) received from the day-ahead market.

### 4.2. Deterministic virtual power plant optimization

The average consumption profiles of electricity used for household water heating are shown in Figure 10. The solid line represents heating in a scenario (benchmark) where the representative household is minimizing its water heating costs individually and is not under the control of the VPP operator. Night-time hours are utilized more often in water heating without the VPP. This difference is observed because, on average, the night-time electricity prices are lower than the daytime prices. In other words, the solid line represents well the inverse average diurnal price profile in the Finnish day-ahead market. It is, however, evident that the heating strategy changes when the VPP operator is allowed to control the EHWH. For instance, more electricity is used during the daytime when solar power generation and possible power imbalances may occur.

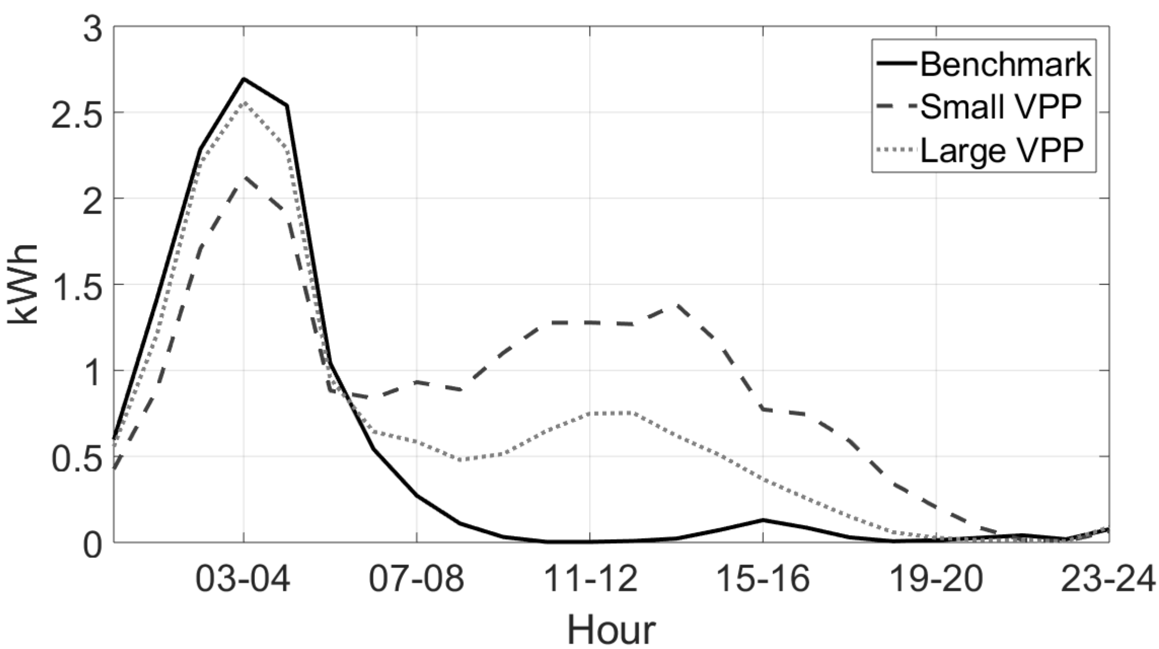


**Figure 10. Average daily hot water heating profiles: household optimizing alone (Benchmark), 5 (small) and 50 (large) households controlled by the VPP operator in the deterministic model.**

The electricity bought from the spot market in the daytime hours provides the resources needed to balance the possible deficit in solar power generation, even though it is a suboptimal strategy from the perspective of cost minimization in water heating. The effect of the VPP optimization is clearly demonstrated in the average daily heating profile with 5 hot water heaters (small VPP). On the other hand, with 50 hot water heaters (large VPP), the effect per single heater is smaller, and the hot water heating electricity profile converges towards the pure cost minimization heating profile of a single household.

More detailed optimization results are shown in Tables 6 and 7. The results marked by delta (Δ) refer to changes compared to the case where hot water heaters and the solar power producer operate in isolation (see Section 2.1). Table 6 shows that the effect of the VPP operations is positive for the system stability, because the demand for imbalance power for both the up- and down-directions are reduced. However, the effect is asymmetric. On average, the VPP operator buys electricity from the grid to balance the negative solar power forecast errors more than it uses the positive forecast errors for water heating. In other words, a "Δ solar power deficit" decreases more than a "Δ solar power surplus". The reason for the asymmetry is that storing the surplus energy in water heaters during the daytime decreases the storage capacity for using cheaper electricity at night.

*Table 6. Deterministic VPP optimization strategy. Difference (delta) to separate the operation of water heaters and solar power imbalance power management.*

| | **N = 5** | **N = 10** | **N = 15** | **N = 20** | **N = 35** | **N = 50** |
|---|---|---|---|---|---|---|
| **Δ solar power deficit (MWh)** | -22.7 (-12.4%) | -36.7 (-20.1%) | -49.5 (-27.1%) | -54.2 (-29.6%) | -88.3 (-48.3%) | -97.2 (-53.2%) |
| **Δ solar power surplus (MWh)** | -6.0 (-4.9%) | -8.9 (-7.4%) | -10.5 (-8.7%) | -11.6 (-9.6%) | -13.0 (-10.8%) | -13.4 (-11.1%) |

In this sense, there is an opportunity cost with respect to using the hot water heater energy capacity for balancing solar power surpluses. The energy storage capacity $\bar{S}$ sets the limit for allocating the solar power surplus to water heaters. On the other hand, in the case of a solar power deficit, no trade-off exists between balancing the deficits and using less expensive night-time hours for water heating.

The VPP can balance the daytime solar power deficit with electricity bought from the grid[21], given that water heaters have enough energy stored to meet the hot water demand. The annual deficit power imbalance is reduced by 12.4%, and the surplus power imbalance is reduced by 4.9%, with five heaters. The effect is stronger as the number of household hot water heaters is increased. More specifically, the deficit power imbalance is reduced by 53.2% and the surplus power imbalance is reduced by 11.1% with 50 heaters.

The water heating costs are increased when heating is optimized in coordination with solar power forecast errors (see Table 7). Conversely, solar power revenues are increased when the VPP operator can internally handle a share of the imbalances caused by the forecast error. The net effect is positive, ranging from 173 € with 5 households to 767 € with 50 households. The monetary gain per household decreases from 34.6 € with 5 hot water heaters to 15.3 € with 50 hot water heaters if the reward is divided evenly between the participating households.

*Table 7. Electricity cost and solar imbalance revenue in deterministic VPP optimization. Difference (delta) to separate the operation of water heaters and solar power imbalance power management.*

| | **N = 5** | **N = 10** | **N = 15** | **N = 20** | **N = 35** | **N = 50** |
|---|---|---|---|---|---|---|
| **Δ electricity cost (€)** | 670.9 | 1098.6 | 1512.3 | 1638.0 | 2806.7 | 3058.9 |
| **Δ solar power imbalance revenue (€)** | 843.9 | 1387.6 | 1892.0 | 2095.2 | 3441.2 | 3825.8 |
| **Net benefit (€):** **Δ revenue – Δ cost** | 173.0 | 289.0 | 379.7 | 457.1 | 634.5 | 767.0 |

Next, stochasticity is introduced to the VPP optimization model. The results show how the uncertainties in the solar forecast error and the imbalance prices change the VPP resource allocation and net benefit of the VPP operation.

### 4.3. Uncertainty in virtual power plant optimization reduces the rewards for households

Figure 11 shows the average daily electricity consumption profiles in the same three scenarios as in Figure 10. Now, the VPP operator is more cautious in using daytime electricity to balance solar power deficits. As a comparison, the VPP operator procures more electricity during daytime hours than in

[21] Note that the profitability of this strategy applies for VPP operations under perfect foresight. As is shown in Section 4.3, the VPP allocation strategy changes as uncertainties with respect to forecast errors and imbalance prices are introduced. This is because the VPP operator must procure more expensive day-time electricity to balance the solar power deficits, but the imbalance direction and imbalance prices are not known in advance.

the cost minimization case of a single household, but not to the same extent as in the deterministic case. This is because the operator must buy (on average) more expensive daytime electricity to balance the solar power deficits, and moreover, it does not know for certain the cost of the forecast error until the end of that hour.

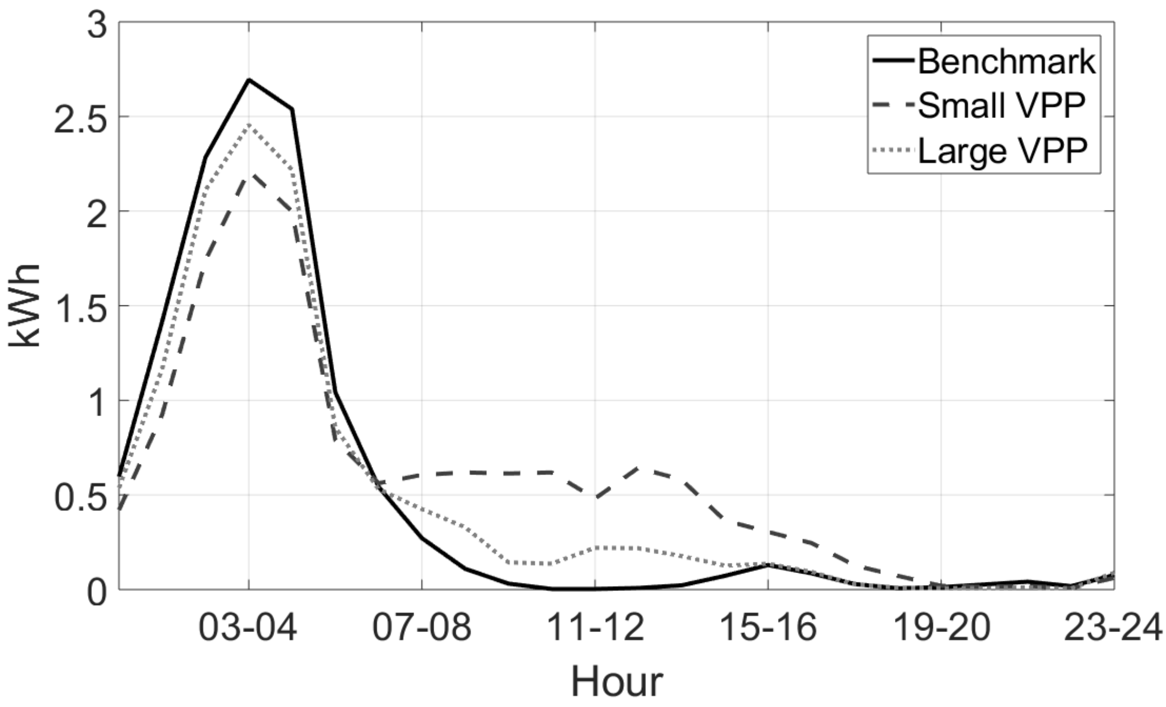


**Figure 11. Average daily hot water heating profiles: household optimizing alone (Benchmark), 5 (small) and 50 (large) households controlled by the VPP operator in the stochastic model.**

Compared to the results of perfect foresight optimization in Table 6, the uncertainties mitigate the VPP's potential to reduce the imbalances in the imbalance power market (see Table 8). Two main differences arise between the deterministic and stochastic optimization strategies. First, the VPP operator handles roughly symmetric amounts of solar power deficits and surpluses. This implies that it does not pay off to the same extent to be prepared to balance the solar power deficits by buying electricity during the daytime hours. Second, the amounts of internally handled deficits and surpluses do not increase as strongly with more demand response resources. The reduction rate in solar power imbalances converges to approximately 10 %.

*Table 8. Stochastic VPP optimization strategy. Difference to separate the operation of water heaters and solar power imbalance power management.*

| | N = 5 | N = 10 | N = 15 | N = 20 | N = 35 | N = 50 |
|---|---|---|---|---|---|---|
| **Δ solar power deficit (MWh)** | -7.4 (-4.1%) | -10.5 (-5.8%) | -12.7 (-7.1%) | -14.3 (-8.0%) | -17.1 (-9.5%) | -18.4 (-10.2%) |
| **Δ solar power surplus (MWh)** | -3.4 (-2.8%) | -5.4 (-4.4%) | -6.9 (-5.5%) | -8.0 (-6.4%) | -10.5 (-8.4%) | -12.0 (-9.6%) |

A solar power plant's forecast error costs are reduced at a diminishing rate (Figure 12). As is shown in Section 4.2, the forecast error cost is 830.3 € without the VPP. In the current case, it is decreased to 674 € with five heaters and decreases to 488.7 € with 50 heaters. The decreased forecast error cost is not, however, the whole story. As the VPP balances more solar deficits than surpluses, the optimized forecast error allocation increases the electricity costs from the grid (see Table 9). Interestingly, the increase in the electricity costs is the highest with 20 households and decreases thereafter. This implies that the VPP operator must buy less electricity per household to be ready to balance the solar power deficits as the number of participating households increases. The net benefit of the VPP, defined as the increase in the solar power imbalance revenue less the increase in the electricity costs for water heating, increases from 37.6 € with 5 households to 252.0 € with 50 households.

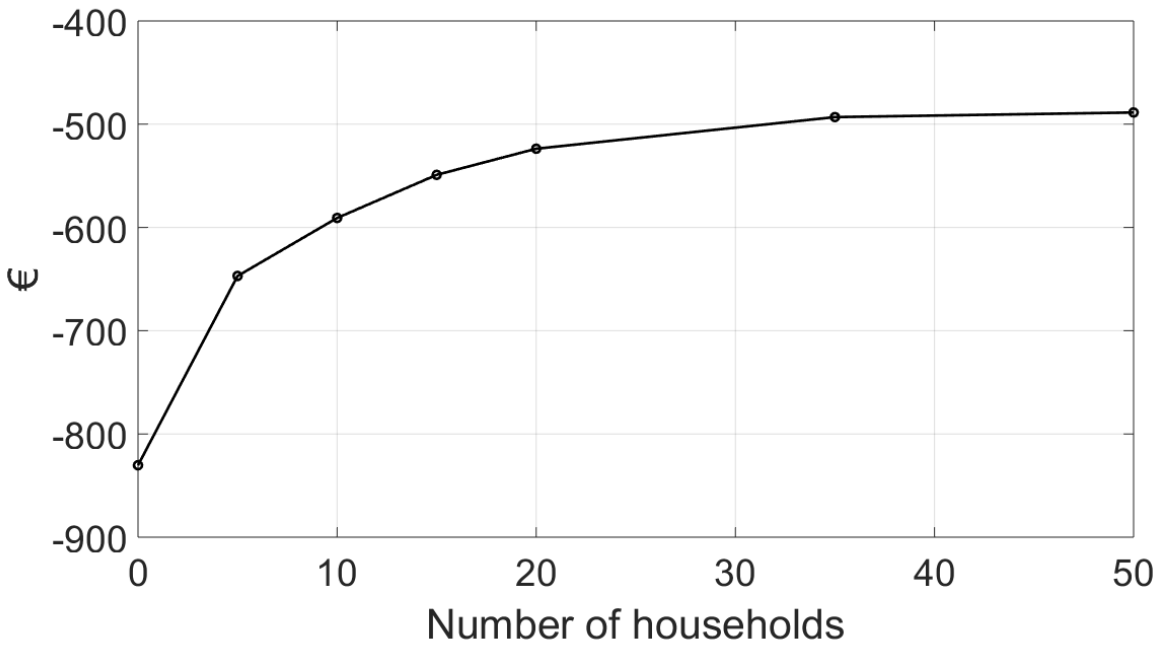


**Figure 12. Solar power plant forecast error cost over different VPP household resources.**

A comparison of the deterministic (Table 7) and stochastic scenarios (Table 9) reveals that the uncertainties related to forecast errors, balancing power market state and imbalance prices greatly decrease the net benefits of the VPP. For instance, the average rewards are decreased by 73% in the stochastic scenarios. However, it must be noted that the rewards are decreased less with a higher number of participating households. With 5 households, the reduction is 78% and with 50 households, the reduction is 67%.

*Table 9. Cost and revenue in stochastic VPP optimization. Difference to separate the operation of water heaters and solar power imbalance power management.*

| | **N = 5** | **N = 10** | **N = 15** | **N = 20** | **N = 35** | **N = 50** |
|---|---|---|---|---|---|---|
| **Δ electricity cost (€)** | 145.7 | 169.1 | 182.3 | 182.5 | 144.8 | 89.6 |
| **Δ solar power imbalance revenue (€)** | 183.3 | 293.5 | 281.3 | 306.6 | 337.2 | 341.7 |
| **Net benefit (€):**<br>**Δ revenue – Δ cost** | **37.6** | **70.4** | **98.9** | **124.1** | **192.4** | **252.0** |

Although the net benefit increases with greater household participation, the average and marginal benefits per member are decreased (see Figure 13). The average benefit is the net benefit divided by the number of households. The marginal benefit is the additional benefit related to new households divided by the number of new households. The values can be interpreted as rewards to households if none of the benefits are allocated to the solar power producer or to the VPP operator. As such, the monetary reward, which ranges from 4.0 to 7.5 euros, is not large on an annual basis. The forecast errors are related to a single 1 MWp solar power plant. Considering different amounts of solar generation resources could lead to an increase in the reward per household[22]. Furthermore, this paper concentrates only on the allocation of solar power forecast errors. Optimizing the day-ahead bidding of PV generation could also improve the value of the VPP operation.

[22] On the other hand, geographic dispersion of PV systems mitigates the aggregated solar generation forecast errors (Tabone et al., 2016), which may decrease the value of resources used to balance supply and demand.

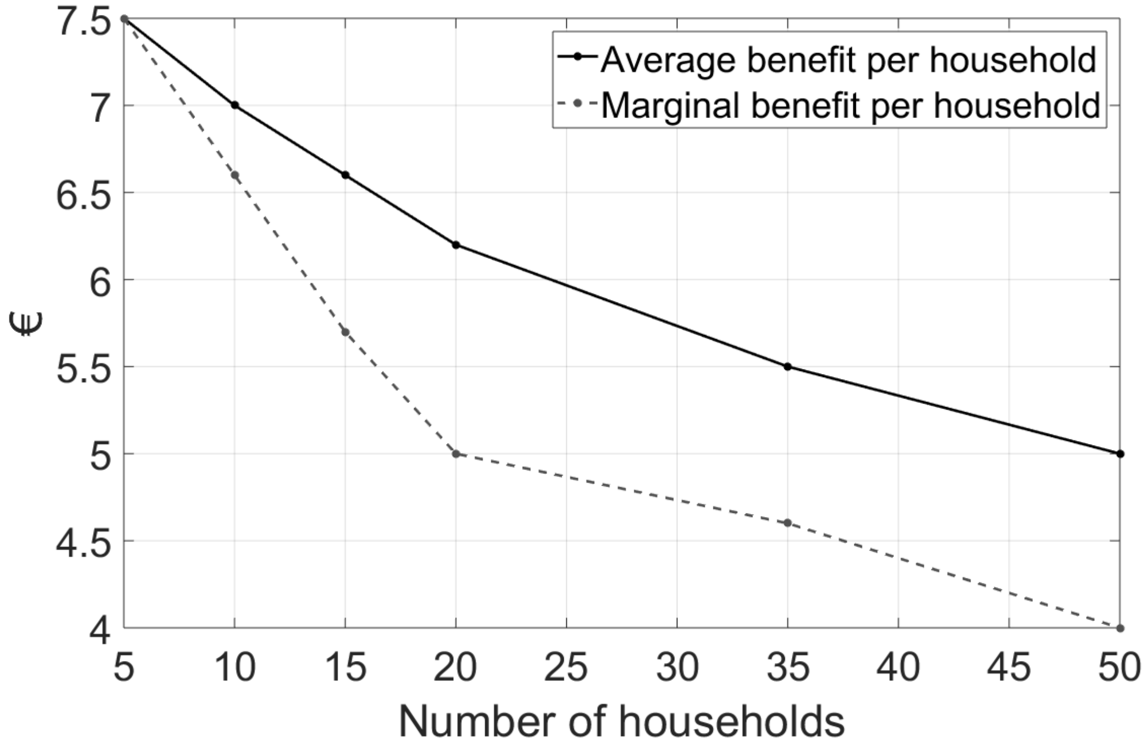


**Figure 13. Average and marginal benefits of household hot water heaters as VPP resources.**

The results suggest interesting topics for further research. For instance, we do not focus on revenue sharing principles nor dynamic pricing related to reaching a certain number of households becoming a part of a VPP. Especially interesting is that the total benefits are increased while the average and marginal benefits are decreased with a higher number of participating households. This finding leads to the question of optimal pricing regime over varying combinations of different kinds of consumption and production resources. How does the VPP incentivize the households to participate initially? What types of value can households with varying consumption patterns offer for the VPP and how are they compensated? To what extent can a VPP improve the self-sufficiency of participating households by matching the electricity consumption and PV generation profile?

It should also be noted that we do not consider the interaction between price formation in day-ahead or balancing power markets and the operations of the VPP. This assumption is justified as long as the VPP can be treated as a price-taker in terms of its amount of resources in relation to the total energy traded. Finally, in this article, we do not consider the other cost components (taxes and grid costs) related to a household's electricity bill. When electricity consumption and the related demand response meet these external cost components in different markets, it will have an impact on the optimal allocation of VPP resources. From the policy perspective, the potentially distorting effect of taxes and grid costs on welfare related to VPP operations is an important future research area.

## 5. Conclusions

To increase the amount of variable renewable energy in the market, flexibility is required from other market participants. The efficiency of the VRE utilization can be increased by optimizing the demand and production resources together. This approach increases the value of the VRE production to the whole energy system. New operators, such as virtual power plants, are needed to coordinate and aggregate active consumer behaviour in the market. There are different possibilities to form a VPP, depending on the specific characteristics of the consumption and production resources. It is important to combine these resources such that the aspects of economies of scale and scope are included when the proper business model is designed.

In this article, we formulate a small-scale virtual power plant that combines a solar power producer and households' electric hot water heaters. The automated demand response in water heating provides a flexible resource that is used to handle the solar power generation imbalances. These imbalances arise from the variable and intermittent nature of solar irradiation, which causes forecasting errors in the day-ahead market scheduling. The objective of the VPP operator is to minimize the combined solar power forecast error and household hot water heating cost.

We find economies of scope as we show that a VPP can add value both by minimizing the hot water heating electricity costs and by utilizing the hot water heaters as a resource in solar power generation imbalance mitigation. In determining the optimal scale of the VPP, our results show that the solar power plant's forecast error costs are reduced at a diminishing rate as we increase the amount of the consumption side resources, and adding more households (50 in our case) does not further increase the benefits for the VPP. Considering that the solar power plant in our case is small, and we consider a fully automated demand response, this exercise is important in showing that a VPP can make a sustainable difference in smart electricity markets, even when only low effort is needed from the consumers of electricity.

In this article, we do not specifically discuss the revenue-sharing dynamics within the VPP. The results imply that this is an interesting topic for further study. In addition, we concentrate only on the hot water heating as a demand response source. A broader view of the total residential heating optimization would be a natural next step in the distributed thermal storage modelling.


## Acknowledgements

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## Appendix A. Stochastic dynamic optimization: virtual power plant operation with solar power and demand response resources

Solar forecast error variable is discretized into $L$ points. Using the hourly solar forecast error data, the uncertainty related to solar power forecast errors is modelled by constructing probability distribution functions for each hour-of-day-by-month pair:

$$e_t \in \{e^1, \dots, e^L | \text{month, hour-of-day}\}, \quad (A1)$$

$$P\left(e_t = e^i\right) = \emptyset(e_i | \text{month, hour-of-day}), i \in \{1,2, \dots, L\}. \quad (A2)$$

Uncertainty related to the state of system balance and imbalance price is modelled by calculating the probabilities of down-, no- and up-regulating states and by formulating probability distributions of down- and up-regulating prices. All the following probabilities and distributions are computed from the historical power market data (see Section 3). The system imbalance state probabilities are calculated separately for every hour-of-day-by-month combinations:

$$IB_t \in \{IB^{down}, IB^{zero}, IB^{up}\}, \quad (A3)$$

$$P(IB_t = IB^d) = \Phi(IB^d | \text{month, hour}), d \in \{\text{down, zero, up}\}. \quad (A4)$$

If the hour is defined as down-regulation hour ($IB_t = IB^{down}$) the imbalance price is below the day-ahead market price by a factor of ($p_t^{down} - p_t^{dam} = \Delta p_t^{down} < 0$), so that the imbalance power price is $p_t^{im} = p_t^{dam} + \Delta p_t^{down}$. Conversely, in up-regulation hour ($IB_t = IB^{up}$) the factor is ($p_t^{up} - p_t^{dam} = \Delta p_t^{up} > 0$) and imbalance power price is $p_t^{im} = p_t^{dam} + \Delta p_t^{up}$. When there is no regulation ($IB_t = IB^{zero}$) the imbalance power price is $p_t^{im} = p_t^{dam}$.

Hourly imbalance price is realized by drawing the price difference of balancing market price to day-ahead market price in the corresponding hour from probability distributions for each hour-of-day-by-month pairs. Distributions are evenly discretized into $M$ points. Formally, for down-regulation prices this is written as:

$$\Delta p_t^{down} \in \left\{\Delta p_1^{down}, \dots, \Delta p_j^{down}\right\}, \quad (A5)$$

$$P\left(\Delta p_t^{down} = \Delta p_j^{down}\right) = \Phi^{down}\left(\Delta p_j^{down} | \text{month, hour-of-day}\right), j \in \{1, \dots, M\}, \quad (A6)$$

and for up-regulation prices as:

$$\Delta p_t^{up} \in \{\Delta p_1^{up}, \dots, \Delta p_k^{up}\}, \qquad (A7)$$

$$P\left(\Delta p_t^{up} = \Delta p_k^{up}\right) = \Phi^{up}\left(\Delta p_k^{up} | \text{month, hour-of-day}\right), k \in \{1, \dots, M\}. \qquad (A8)$$

Given the uncertainties related to solar forecast errors, system balance state and imbalance prices, the stochastic dynamic optimization problem of the VPP operation is:

$$V_t(S_t) = \max_{x_t}\left\{-\left(x_t p_t^{dam}\right) + \beta V_{t+1}(S_{t+1})\right\}, \qquad (A9)$$

when the sun is below the horizon, and:

$$V_t(S_t) = \max_{x_t} \sum_{i=1}^{L} \emptyset(e_i)$$

$$\left\{-\left(x_t p_t^{dam}\right) + \sum_{d\ \in \{\text{down,zero,up}\}} \Phi(IB^d)\left\{\max_{e_t^{VPP}} RevIB\left(e_t - e_t^{vpp}\right) + \beta V_{t+1}(S_{t+1})\right\}\right\}, \qquad (A10)$$

when the sun is above the horizon, subject to

$$0 \le x_t \le \bar{x}, \qquad (A11)$$

and

$$0 \le S_{t+1} = S_t - c_t - L(S_t) + x_t - e_t^{vpp} \le \bar{S}. \qquad (A12)$$

The constraints for internal balancing of forecast errors within the VPP ($e_t^{vpp}$) are

$$max\left(e_t, S_t - c_t - L(S_t) + x_t - \bar{S}\right) \le e_t^{vpp} \le 0, \text{ if } e_t < 0, \qquad (A13)$$

$$0 \le e_t^{vpp} \le min(e_t, x_t, S_t - c_t - L(S_t) + x_t), \text{ if } e_t > 0. \qquad (A14)$$

The expected revenue from imbalance market *RevIB* is set as follows

- when $e_t < 0$ and $IB_t \in \{IB^{zero}, IB^{up}\}$

$$RevIB\left(e_t^{vpp}|e_t\right) = -\left(e_t - e_t^{vpp}\right)p_t^{dam}, \qquad (A15)$$

- when $e_t < 0$ and $IB_t = IB^{down}$

$$RevIB\left(e_t^{vpp}|e_t\right) = \sum_{j=1}^{M} \Phi^{down}\left(\Delta p_j^{down}\right) \cdot \left(e_t - e_t^{vpp}\right) \cdot \left(p_t^{dam} + \Delta p_j^{down}\right), \qquad (A16)$$

- when $e_t > 0$ and $IB_t \in \{IB^{down}, IB^{zero}\}$

$$RevIB\left(e_t^{vpp}|e_t\right) = e_t p_t^{dam} - \left(e_t - e_t^{vpp}\right)p_t^{dam}, \qquad (A17)$$

- when $e_t > 0$ and $IB_t = IB^{up}$

$$RevIB\left(e_t^{vpp}|e_t\right) = \sum_{k=1}^{M} \Phi^{up}\left(\Delta p_k^{up}\right)\left\{e_t p_t^{dam} - \left(e_t - e_t^{vpp}\right) \cdot \left(p_t^{dam} + \Delta p_k^{up}\right)\right\}. \qquad (A18)$$

As discussed previously, the hourly optimization problem is deterministic with respect to the heating costs and hot water energy content dynamics in hours when sun is below the horizon (see Equation A9). On the other hand, the optimization problem is stochastic in hours with possible solar power production and forecast errors (see Equation A10). Uncertainty at the first stage is related to the hourly solar power forecast error realization $(e_t)$. VPP operator maximizes the expected imbalance revenue less the EHWH heating costs by optimizing the use of electricity from the grid $(x_t)$. Uncertainty at the second stage is related to the system imbalance direction and imbalance price revealed after the hour. Given the forecast error realization, the VPP chooses the optimal amount of forecast error balanced internally within the VPP $(e_t^{vpp})$, given the probability distribution of revenue in the imbalance power market.

Analogously to the description given in Section 2.1, if the realized solar power output is higher than the forecasted $(e_t < 0)$, the VPP operator may absorb the excess generation in its controllable heaters depending on the amount of free storage in them (see Equation A13). If the realized solar power output is lower than the forecasted $(e_t > 0)$, the VPP operator can choose not to utilize contracted electricity from the grid in water heating while ensuring that all heated water demand can be supplied (see Equation A14). The imbalance market revenue in two-price system (Equations A15 – A18) is explained in Section 2.1.1.

## REFERENCES


Akasiadis, C., Chalkiadakis, G., 2017. Cooperative electricity consumption shifting. Sustainable Energy, Grids and Networks 9, 38-58.

Barsali, S., Giglioli, R., Lutzemberger, G., Poli, D., Valenti, G., 2017. Optimised operation of storage systems integrated with MW photovoltaic plants, considering the impact on the battery lifetime. Journal of Energy Storage 12, 178–185.

Bengtsson, L., Andrae, U., Aspelien, T., Batrak, Y., Calvo, J., de Rooy, W., Gleeson, E., Hansen-Sass, B., Homleid, M., Hortal, M., Ivarsson, K., Lenderink, G., Niemelä, S., Nielsen, K. P. Onvlee, J., Rontu, L., Samuelsson, P., Muñoz, D. S., Subias, A., Tijm, S., Toll, V., Yang, X., Køltzow, M. Ø., 2017. The HARMONIE–AROME Model Configuration in the ALADIN–HIRLAM NWP System.Monthly Weather Review, 145(5), 1919–1935. https://doi.org/10.1175/MWR-D-16-0417.1

Borenstein, S., Jaske, M., Rosenfeld, A., 2002. Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets. UC Berkeley: Center for the Study of Energy Markets.

Campaigne, C., Oren, S. S., 2016. Firming renewable power with demand response: an end-to-end aggregator business model. Journal of Regulatory Economics 50, 1–37.

Chaves-Ávila, J. P., Hakvoort, R. A., Ramos, A., 2014. The impact of European balancing rules on wind power economics and on short-term bidding strategies. Energy Policy 68, 383–393.

Coase, R., 1973. The nature of the firm. Economica 4, 386–405.

Dabbagh, S. R., Sheikh-El-Eslami, M. K., 2015. Risk-based profit allocation to DERs integrated with a virtual power plant using cooperative Game theory. Electric Power Systems Research 121, 368–378.

eSett, 2018. Nordic Imbalance Settlement Handbook – Instructions and Rules for Market Participants. Available at https://www.esett.com/handbook/ (Accessed 18th of July 2018).

Faruqui, A., Harris, D., Hledik, R., 2010. Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investments. Energy Policy 38, 6222–6231.

Fingrid, 2018. Balancing energy and balancing capacity markets. https://www.fingrid.fi/en/electricity-market/reserves_and_balancing/balancing-energy-and-balancing-capacity-markets/#balancing-energy-pricing

Finn, P., Fitzpatrick, C., Connolly, D., Leahy, M., Relihan, L., 2011. Facilitation of renewable electricity using price based appliance control in Ireland's electricity market. Energy 36, 2952–2960.

Gowrisankaran, G., Reynolds, S., Samano, M., 2016. Intermittency and the Value of Renewable Energy. Journal of Political Economy 124, 1187–1234.

Henten, A. H., Windekilde, I. M., 2016. Transaction costs and the sharing economy. Info 18, 1–15.

Hirth, L., 2013. The market value of variable renewables: The effect of solar wind power variability on their relative price. Energy Economics 38, 218–236.

Hirth, L., 2015. Market value of solar power: Is photovoltaics cost-competitive? IET Renewable Power Generation 9, 37–45.

Hirth, L., 2016. The benefits of flexibility: The value of wind energy with hydropower. Applied Energy 181, 210–223.

Hirth, L., Ueckerdt, F., Edenhofer, O., 2015. Integration costs revisited – An economic framework for wind and solar variability. Renewable Energy 74, 925–939.

Hirvonen, J., Kayo, G., Hasan, A., Siren, K., 2016. Zero energy level and economic potential of small-scale building-integrated PV with different heating systems in Nordic conditions. Applied Energy 167, 255–269.

Hobman, E. V., Frederiks, E. R., Stenner, K., Meikle, S., 2016. Uptake and usage of cost-reflective electricity pricing: Insights from psychology and behavioural economics. Renewable and Sustainable Energy Reviews 57, 455–467.

Holttinen, H., Meibom, P., Orths, A., Lange, B., O'Malley, M., Tande, J. O., Estanqueiro, A., Gomez, E., Söder, L., Strbac, G., Smith, J. C., van Hulle, F., 2011. Impacts of large amounts of wind power on design and operation of power systems, results of IEA collaboration. Wind Energy 14, 179–192.

Huuki, H., Karhinen, S., Kopsakangas-Savolainen, M., Svento, R., 2017. Flexible demand and flexible supply as enablers of variable energy integration. Available at Social Science Research Network: https://ssrn.com/abstract=2966053 or http://dx.doi.org/10.2139/ssrn.2966053.

Jordan, U., Vajen, K., 2017. Tool for the generation of domestic hot water profiles on a statistical basis. Manual. http://www.solar.uni-kassel.de

Kairies, K.-P., Figgener, J., Haberschusz, D., Wessels, O., Tepe, B., Sauer, D. U., 2019. Market and technology development of PV home storage systems in Germany. Journal of Energy Storage 23, 416–424.

Kapsalis, V., Hadellis, L., 2017. Optimal operation scheduling of electric hot water heaters under dynamic pricing. Sustainable Cities and Society 31, 109-121.

Karhinen, S., Huuki, H., 2017. Private and Social Benefits of a Pumped Hydro Energy Storage with Increasing Amount of Wind Power. Energy Economics 81, 942–959.

Karhinen, S., Huuki, H., Ruokamo, E., 2018. Emissions reduction by dynamic optimization of distributed energy storage under aggregator's control. Available at Social Science Research Network:

Katz, J., Andersen, F. M., Morthorst, P. E., 2016. Load-shift incentives for household demand response: Evaluation of hourly dynamic pricing and rebate schemes in a wind-based electricity system. Energy 115, 1602–1616.

Kenney, M., Zysman, J., 2016. The Rise of Platform Economy. Issues in Science and Technology. XXXII (3). http://issues.org/32-3/the-rise-of-the-platform-economy/.

Kepplinger, P., Huber, G., Petrasch, J., 2015. Autonomous optimal control for demand side management with resistive domestic hot water heaters using linear optimization. Energy and Buildings 100, 50–55.

Koohi-Fayegh, S., Rosen, M. A., 2020. A review of energy storage types, applications and recent developments. Journal of Energy Storage 27, 101047.

Krishnamurthy, C., K., B., Vesterberg, M., Böök, H., Lindfors A. V., Svento R. 2018. Real-time pricing revisited: Demand flexibility in the presence of micro-generation. Energy Policy 123, 642-658. https://doi.org/10.1016/j.enpol.2018.08.024

Luo, X., Wang, J., Dooner, M., Clarke, J., 2015. Overview of current development in electrical energy storage technologies and the application potential in power system operation. Applied Energy 137, 511–536.

Martin, C. J., 2016. The sharing economy: A pathway to sustainability or a nightmarish form of neoliberal capitalism? Ecological Economics 121, 149–159.

Martinez-Anido, C. B., Botor, B., Florita, A. R., Draxl, C., Lu, S., Hamann, H. F., Hodge, B.-M., 2016. The value of day-ahead solar power forecasting improvement. Solar Energy 129, 192–203.

McPherson, M., Johnson, N., Strubegger, M., 2018. The role of electricity storage and hydrogen technologies in enabling global low-carbon energy transitions. Applied Energy 216, 649–661.

Nosratabadi, S. M., Hooshmand, R.-A., Gholipour, E., 2017. A comprehensive review on microgrid and virtual power plant concepts employed for distributed energy resources scheduling in power systems. Renewable and Sustainable Energy Reviews 67, 341–363.

Nunes, P., Farias, T. Brito, M. C., 2015. Enabling solar electricity with electric vehicles smart charging. Energy 87, 10-20.

Pena-Bello, A., Burer, M., Patel, M. K., Parra, D., 2017. Optimizing PV and grid charging in combined applications to improve the profitability of residential batteries. Journal of Energy Storage 13, 58–72.

Shafie-khan, M., Moghaddam, M. P., Sheikh-El-Eslami, M. K. (2013). Development of a virtual power plant market model to investigate strategic and collusive behavior of market players. Energy Policy 61, 717–728.

Schröder, T., Kuckshinrichs, W., 2015. Value of lost load: An efficient economic indicator for power supply security? A literature review. Frontiers in Energy Research, 3–55.

Staffell, I. & Rustomji, M., 2016. Maximizing the value of electricity storage. Journal of Energy Storage 8, 212–225.

Tabone, M, Goebel, C, Callaway, D. S., 2016. The effect of PV siting on power system flexibility needs. Solar Energy 139, 776-786.

Tajeddini, M. A., Rahimi-Khan, A., Soroudi, A., 2014. Risk averse optimal operation of a virtual power plant using two stage stochastic programming. Energy 73, 958–967.

Tascikaraoglu, A., Erdinc, O., Uzunoglu, M., Karakas, A., 2014. An adaptive load dispatching and forecasting strategy for a virtual power plant including renewable energy conversion units. Applied Energy 119, 445–453.

Thavlov, A., Bindner, H. W., 2015. Utilization of Flexible Demand in a Virtual Power Plant Set-Up. IEEE Transactions on Smart Grid 6, 640–647.

Thieblemont, H., Haghighat, F., Ooka, R., Moreau, A., 2017. Predictive control strategies based on weather forecast in buildings with energy storage system: A review of the state-of-the-art. Energy and Buildings 153, 485–500.

Torriti, J., Hassan, M. G., Leach, M., 2010. Demand response experience in Europe: policies, programmes and implementation. Energy 35, 1575–1583.

Vanthournout, K., D'hulst, R., Geysen, D., Jacobs, G., 2012. A Smart Domestic Hot Water Buffer. IEEE Transactions on Smart Grid 3, 2121–2127.

Vega, A. M., Santamaria, F, Rivas, E., 2015. Modeling for home electric energy management: A review. Renewable and Sustainable Energy Reviews 52, 948-959.

Verbeke, S., Audenaert, A., 2018. Thermal inertia in buildings: A review of impacts across climate and building use. Renewable and Sustainable Energy Reviews 82, 2300–2318.

Wissner, M., 2011. The Smart Grid – A saucerful of secrets? Applied Energy 88, 2509–2518.

Xia, S., Chan, K. W., Luo, X., Bu, S., Ding, Z., Zhou, B., 2018. Optimal sizing of energy storage system and its cost-benefit analysis for power grid planning with intermittent wind generation. Renewable Energy 122, 472–486.

Zervas, G., Proserpio, D., Byers, J. W., 2017. The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. Journal of Marketing Research 54, 687–705.