# Predictive control for multi-market trade of aggregated demand response using a black box approach

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# Predictive Control for Multi-Market Trade of Aggregated Demand Response using a Black Box Approach

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*Abstract*—**Aggregated demand response for smart grid services is a growing field of interest especially for market participation. To minimize economic and network instability risks, flexibility characteristics such as shiftable capacity must be known. This is traditionally done using lower level, end user, device specifications. However, with these large numbers, having lower level information, has both privacy and computational limitations. Previous studies have shown that black box forecasting of shiftable capacity, using machine learning techniques, can be done accurately for a homogeneous cluster of heating devices. This paper validates the machine learning model for a heterogeneous virtual power plant. Further it applies this model to a control strategy to offer flexibility on an imbalance market while maintaining day ahead market obligations profitably. It is shown that using a black box approach 89% optimal economic performance is met. Further, by combining profits made on imbalance market and the day ahead costs, the overall monthly electricity costs are reduced 20%.**

*Index Terms*—**Predictive Control, Machine Learning, Virtual Power Plants, Flexibility, Demand Response, Energy Markets.**

## I. Introduction

AGGREGATOR services for electricity market trade is a growing trend in the energy sector. With fast growing technologies in residential demand response and energy storage it is becoming more viable to allow aggregated residential flexibility to actively participate on the wholesale markets. Many works have investigated bottom up and grey box techniques which pose not only computational time constraints but also end user privacy. Further, limited work investigates black box aggregated demand response characterization with a combination of multiple shiftable devices, i.e. a heterogeneous virtual power plant (VPP). This paper aims at showing that black box machine learning of flexibility capacity for heterogeneous clusters can be achieved with high accuracy. Further it aims to combine machine learning techniques with a multi-objective control technique. Three approaches are investigated: real time coordination with no forecasting of VPP flexibility, machine learned flexibility coupled to the control strategy and finally a best case scenario is simulated with a perfect forecast of VPP as well as knowledge of future electricity prices. This is conducted with a cluster of 1000 households trading both on the day ahead and an imbalance market. It is found that flexibility capacity of a heterogeneous VPP can be forecasted with an average error of 4%. Also, when applying this capacity knowledge to a trade strategy up to 89% of optimum can be realized. This profit recovers up to 20% of the costs from the day ahead market for one month of trading.

## II. Related Work

Previous works have investigated residential VPP market operation strategies. In [1] and [2], model predictive control (MPC) techniques are used to optimize trading on multiple energy markets. These approaches focus on prediction of VPP behavior in response to price incentives as well as external factors such as weather and historic electricity consumption. Additionally in [3], a grey-box dual coordination mechanism is investigated for multi-market trade of a homogeneous VPP of 1000 plug in electric vehicles.

Quantifying the availability of a residential VPP flexibility using detailed lower level information has been used to accurately offer aggregate small demand response [4]. Also, grey box techniques for flexibility assessments where some lower level information, such as state of charge (SOC), have been used to estimate the aggregate flexibility capacity [6]. Further in [5], machine learning was utilized to forecast the real time flexible capacity available. This was done with a homogeneous cluster of heat pumps using a top down, black box approach.

This work proposes a top down, black box approach to model and estimate real time available flexibility of a heterogeneous VPP and using that knowledge to optimize for both day ahead and imbalance market trade.

## III. Models

To test and validate a multi-market control strategy in the simulation environment a number of models are employed. The models considered are: the virtual power plant, electricity markets, the individual devices, user behaviour within that virtual power plant and finally the machine learning model used to forecast the flexibility capacity.

## A. Device Models

To simulate a heterogeneous virtual power plant, a set of validated device models and smart controllers are used. The devices modelled are smart controlled heating devices (heat pump and micro-CHP (combined heat and power)), white goods (dish washers, washing machines and dryers), cold storage (such as refrigerators and freezers), and small renewable generation (photovoltaics and wind turbine). Further an energy pattern generator which generates non-shiftable base electricity load profile, tap water and space heating demand patterns. Mathematical models for all devices are fully described in [7]. The validation of load and heat demand profiles can be found in [8], white goods and cold store in [9] and that of the heating devices in [5].

## B. Virtual Power Plant

An aggregator bundles flexibility capabilities of distributed generation and demand response and offers the collective resources for smart grid services such as ancillary, e.g. congestion management, as well as active electricity market participation. This technical aggregation is referred to as a Virtual Power Plant (VPP).

The smart control algorithm applied in this study, the PowerMatcher, is a decentralized coordination mechanism which integrates demand and supply flexibility in the operation of the electricity system [9]. Each device is equipped with a smart controller which uses price incentives to coordinate in real-time the devices' flexibility within the comfort boundaries. The only information that is exchanged between the device agents and the control algorithms are bids. These bids express to what degree an agent is willing to pay or be paid for a certain amount of electricity and can also be easily aggregated. In this way the end users privacy can be protected while still offering demand response services. The smart controllers as well as bid formations for all devices are fully described in [7], [9], and [8].

## C. Electricity Markets

The electricity markets focused on in this study are the day ahead spot market, and the imbalance market. These are based on the current Dutch energy markets.

*1) Day Ahead Market:* The day-ahead market allows trading of electricity with a timespan of 14 days up to one day prior to delivery. Anonymous supply and demand bids are made for every hour of day D. At 12 am, on D-1, the market is cleared and a uniform price for every hour is established. In the Netherlands the day ahead power exchange is APX Power NL Day-Ahead Market

*2) Imbalance Market:* In the Netherlands, if a Balancing Responsible Party (BRP) is not able to maintain a balanced portfolio, the transmission system operator (TSO) activates reserve capacity. This fee for this service depends on the total imbalance of the TSOs control area and the imbalance of the BRP as shown in Table I. The total activated reserve is called net regulating volume (NRV), which is positive when upward reserve is required and negative for downward reserve. The maximum incremental price (MIP) is the maximum price paid by the TSO to activate upward reserve. The minimum price paid to the TSO for downward reserve is called the minimum decremental price (MDP) and an administrative fee depending on the total system imbalance.

TABLE I
IMBALANCE TARIFF DEPENDING ON SYSTEM SHORTAGE/EXCESS.

|  | NRV>0 | NRV<0 |
|---|---|---|
| Positive BRP Imbalance | MDP- $\alpha$ | MIP |
| Negative BRP Imbalance | MDP | MIP + $\alpha$ |

The Dutch TSO TenneT publishes the bidding ladder (see Figure 1) as well as the most recently deployed regulating and reserve power on a minute by minute basis (so-called balance delta), which provides an indication of the settlement prices. Using this, BRPs can choose to regulate against the imbalance in the form of passive contribution, i.e. they counteract the imbalance without being activated through the bidding ladder but can still receive remuneration.
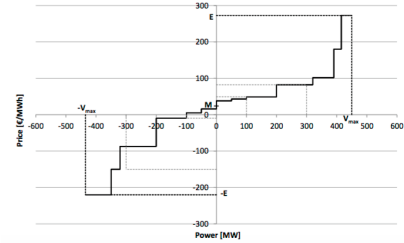


Fig. 1. Schematic of Dutch Control Reserve Bidding Ladder. [10]

## D. Machine Learning Model

As was stated, previous works have proved the validity of machine learning for prediction of a homogeneous VPPs' capacity, see [5]. The machine learning technique yielding the most accurate result was a single hidden layer artificial neural network (ANN). ANN is a pattern recognition technique which is used when the domain of the problem is not entirely known. A supervised ANN is able to represent non-linear relationships between the input and output data by training the hidden layer of neurons with previously recorded data representing a desired relationship (training set).
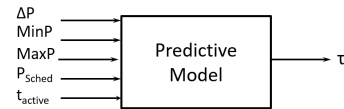


Fig. 2. Data Input and Output of the Predictive Model.

A single hidden layer neural network with sigmoid transfer function, as presented in [5] was used to represent the described model. With the input data being: ramp power ($\Delta P$), which is the requested deviation power from the current day ached scheduled power, scheduled activation time ($t_{active}$),

day ahead schedule power at time of activation ($P_{Sched}$), maximum and minimum bid ($MaxP$ and $MinP$), and output longevity ($\tau$), that is the length of time the provided ramp power can be sustained.

## IV. CONTROL OPTIMIZATION ALGORITHM

A simple control strategy was designed which could be applied for all three cases: without forecasting of shiftable capacity, machine learned capacity and that with the perfect forecast of VPP shiftable capacity and market prices. All three approaches use a pre-determined day ahead schedule defined in Section V which is generated to optimally perform to the day ahead APX prices. A general overview of the connection to markets can be seen in Figure 3.
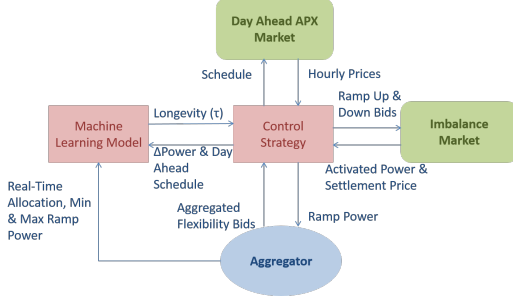
Fig. 3.  Connection to Markets.

### A. Assumptions and Constraints

A number of assumptions and constraints are defined for this control strategy itemized below:

- The imbalance market is a dual pricing system for short and long offers like that of the Dutch balancing market.
- The market will operate on a 15 minute time slot.
- The administration fee, $\alpha$, will be neglected for imbalances.

To ensure profitability as well as stability in the network constraints are defined for the control strategy:

- The VPP will ramp up only for negative prices.
- The ramp down marginal cost must be higher than the current APX price.
- The VPP must consider future, day ahead schedule, requirements in trade.
- The VPP cannot offer ramp power outside the bounds of the aggregated bid.

### B. Trading Strategy

The trading strategy will be repeated on a 15 minute time scale. Firstly the total ramp up, $\uparrow E_{Total}$, and down energy capacity, $\downarrow E_{Total}$, is calculated. This is done differently for all three approaches. For the no forecasting approach, the ramp up capacity is estimated using Equation (1):

$$\uparrow E_{total} = \begin{cases} (P_{Max} - P_{Sched}).\Delta t < 0, & (P_{Max} - P_{Sched}).\Delta t \\ else, & 0 \end{cases} \tag{1}$$
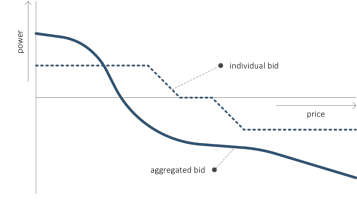
Fig. 4.  The Aggregated Bid of the VPP. [9]

With $P_{Max}$ being the current maximum ramp power of the VPP aggregated bid as seen in Figure 4, $P_{Sched}$ the current day ahead scheduled power and $\Delta t$ the time interval of the imbalance market, 0.25 hours (15 minutes). Similarly, the ramp down capacity is estimated using Equation (2):

$$\downarrow E_{total} = \begin{cases} (P_{Sched} - P_{Min}).\Delta t < 0, & (P_{Sched} - P_{Min}).\Delta t \\ else, & 0 \end{cases} \tag{2}$$

With $P_{Min}$ being the current minimum ramp power of the VPP aggregated bid.

The machine learning model approach, described in sub-section VI-B, returns the $\tau$ for the given ramp up power, $P_{Max} - P_{Sched}$ and ramp down power $P_{Sched} - P_{Min}$ provided they are greater than zero. In this case, the associated $E_{Total}$ is set to zero and unavailable for imbalance trade.

Finally, for the perfect forecast approach, the $\uparrow E_{Total}$ and $\downarrow E_{Total}$ are calculated using a bottom up approach, where every device, in addition to their priority bid, sends their shiftable ramp up and down energy capacity which is aggregated at the top level. This energy capacity is calculated with full knowledge of the future heat and electricity demands of the device. To ensure the flexibility capacity is reserved for the future day ahead schedule, the amount of ramp up and down energy required to meet the day ahead schedule for the next hour is calculated in Equations (3) and (4) with $P_{Alloc}$ being the current total allocation of the VPP:

$$\uparrow E_{Sched} = \sum_{t=1}^{n} \begin{cases} P_{Sched}(t) < P_{Max} \wedge, & (P_{Sched}(t) - P_{Alloc}).\Delta t \\ P_{Alloc} > P_{Sched}(t) \\ else, & 0 \end{cases} \tag{3}$$

&

$$\downarrow E_{Sched} = \sum_{t=1}^{n} \begin{cases} P_{Sched}(t) > P_{Min} \wedge, & (P_{Alloc} - P_{Sched}(t)).\Delta t \\ P_{Alloc} > P_{Sched}(t) \\ Else, & 0 \end{cases} \tag{4}$$

From this the available energy which can be traded for imbalance is calculated:

$$\uparrow E_{Avail} = (\uparrow E_{Total} - \uparrow E_{Sched}) \tag{5}$$

&

$$\downarrow E_{Avail} = (\downarrow E_{Total} - \uparrow E_{Sched}) \tag{6}$$

The approaches: No Forecasting and Machine Learned Capacity, use the previous day minimum and maximum imbalance prices for short and long. While, the perfect forecast is

given the future imbalance prices for the current day. Using the estimated imbalance price bounds, a linear mapping between the maximum of the previous days $E_{avail}$ is to calculate the minimum cost for ramp up and down services.

$$\downarrow C_m = (\frac{\downarrow E_{max}(d-1)}{C_{APX} - \downarrow max(C_I(d-1))}).\downarrow E_{Avail} + C_{APX} \quad (7)$$

&

$$\uparrow C_m = (\frac{\uparrow E_{max}(d-1)}{\uparrow min(C_I(d-1))}).\uparrow E_{Avail} \quad (8)$$

Note: if in Equation (8), $\uparrow min(C_I(d-1)$ is not negative, the last day $(d-2,...)$ with a negative price will be used.

To trade on the imbalance market, two individual bids consisting of an array of power and price (€/MWh), for ramp up and down services, are then generated. To do this a price will be assigned for each power step between zero and $P_{Avail}$ which is $E_{avail}$ / $\Delta t$. Finally, $\downarrow C(n)$ and $\uparrow C(n)$ are calculated with (9) and (10) where $n = 0 \rightarrow P_{Avail}$, the power steps in the offered bids.

$$\downarrow C(n) = (\frac{\downarrow maxC_I(d-1) - \downarrow C_m}{\downarrow P_{avail}}).n + \downarrow C_m \quad (9)$$

&

$$\uparrow C(n) = (\frac{\uparrow C_m - \uparrow min(C_I(d-1)}{-\uparrow P_{avail}}).n + \uparrow C_m \quad (10)$$

## V. SCENARIO

A simulation of 1000 individual households is created. Its design is an extended version of a field trial in Hoogkerk, The Netherlands, consisting of 22 smart equipped households. [12]. Each home has its own individual generated base, non-flexible electricity profile as well as individual heat and tap water demand profiles. These profiles are created using TNO's energy pattern generator, a validated software tool [8], that produces high resolution electricity and heat demand profiles. Each household is equipped with a flexibly controlled heating device, 800 heat pumps and 200 micro-CHPs, each of which was attached to a 110 liter spaced heating buffer and 90 liter tap water buffer. Additionally, the penetration of white good devices is based on a Dutch survey [11] and can be seen in Table II.

TABLE II
1000 HOUSEHOLD HETEROGENEOUS CLUSTER MAKE-UP.

| Appliance | Penetration (%) |
|---|---|
| Refrigerator | 100 |
| Freezer | 79 |
| Dishwasher | 47 |
| Washing Machine | 100 |
| Tumble Dryer | 59 |
| Heat Pump | 80 |
| Micro-CHP | 20 |

Further as in PowerMatching city, every household is equipped with a small photovoltaic (PV) panel. For this, real PV measurements in The Netherlands are utilized and scaled to match that of 1000 households (1240 kW nominal electric

power). Finally, the amount of offshore and onshore wind in the simulations is based on the WLO-SE (Welfare and Living Environment) scenarios on energy supply and demand with a time horizon up to 2040 [13].

The three control strategies are run for one month (March) using real day ahead, APX, prices taken from previous year. Further, real TSO imbalance prices and volumes, from the Dutch TSO TenneT, during the same time period are used. To generate the day ahead schedule, using day ahead APX prices as incentives, the cluster is steered by the PowerMatcher, the cluster responds accordingly. The responding aggregated active power behavior profile is then averaged to a 15 minute resolution to create an optimal day ahead schedule for this price profile. In Figure 5, a depiction of the APX prices and the day ahead schedule generated can be seen.
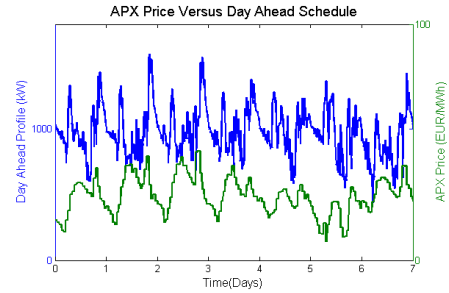


Fig. 5. APX Price with associated day ahead schedule for one week.

As day ahead, imbalance price settlement is done in a 15 minute resolution. When the control strategies negatively contribute to an imbalance a financial profit is the result (e.g. system is short and aggregator is long), if the aggregator contributes to an imbalance the result is a financial cost.

## VI. VALIDATION

Section IV describes the control strategy which is used for offering flexibility on the imbalance market. This control strategy was applied with three variations. Firstly, the no forecasting, which uses only the real time maximum and minimum ramp power to estimate flexible capacity. Secondly, the machine learned capacity, which uses a supervised neural network model to predict the available capacity. Finally, the perfect forecast, which uses lower level device state information as well as future demand and price data to optimally trade on the imbalance market. Below will describe the modifications in strategy, validation process and data required for each approach.

### A. No Forecasting

Using marginal cost and trading strategy described in Section IV, a few simplifications are made to allow for lack of flexibility capacity. Firstly, it is assumed that full ramp capacity can be met in the 15 minute time slot. Therefore the $\Delta P$ up is the difference between day ahead and maximum power in aggregated bid. The maximum ramp down power is the difference between the minimum bid power and day

ahead schedule, assuming minimum is less than the day ahead schedule. The constraint for future day ahead schedule is done by evaluating if the current VPP conditions could perform at the future scheduled power. To estimate the upper and lower bounds for the imbalance prices, the minimum and maximum from the previous day are used.

### B. Machine Learned Capacity

The training and validation set for the ANN model used the cluster scenario described in Section V. A 1000 household heterogeneous VPP with a mix of heat pumps, micro-CHPs, white goods and cold storage units are used for flexible devices. The VPP follows a pre-determined day ahead schedule and ramp powers are deviation requests from this day ahead profile. From this, the model estimates the longevity $\tau$, the amount of time the VPP can hold a ramp power, and thus estimate the shiftable capacity of the certain ramp direction.

For both the training and validation set of clusters, a random ramp power, between -100 and 100kW, was assigned. Further, a ramp power was assigned at various hours of the day and requested to hold for the remainder of the day. The data set consists of 2000 observations divided into two sets, training and validation. The training data is a random sample drawn from the input data (1500 rows of data). The rest of the data from the input set (500 rows of data) is used for model validation. After training, as shown in Figure 2, the machine model is given a day ahead schedule of the cluster as well at the ramp power at a given time and asked to estimate the ramp longevity $\tau$. These scenarios were then simulated to validate $\tau$ for each case.
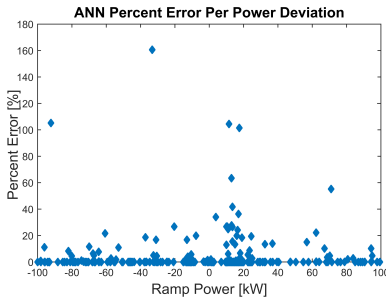


Fig. 6. Percent Error versus Ramp Power of Capacity Prediction for ANN Algorithm.

Figure 6 depicts the error seen over the validation set. Although there are a few outliers, it is seen that the average error over all sets is 4.28%. When comparing to that [5] with a slightly lower average error of 2.3%. This model was then used to estimate the ramp up and down capacity during runtime as described in Section IV. As is done in the no-forecast strategy, the minimum and maximum imbalance prices for the day are taken the previous day.

### C. Perfect Forecast

The perfect forecast control provides best case scenario for steering a VPP for imbalance trade. Here every 15 minutes the individual shiftable energy per device is calculated and aggregated. This is done using the known future demand and user behaviour. For example, heat demand for the next 15 minutes as well as inflexible household load will be known to give an exact amount of ramp up and down energy capacity from the day ahead schedule. Further, the maximum and minimum imbalance prices for that day are known before trading. While this is an unrealistic scenario it gives an upper bound on assessing the benefit of using forecasted flexibility in a control strategy.

## VII. RESULTS

The three strategies; no forecast, machine learned capacity and perfect forecast for the scenarios described in section V were simulated for the entire month of March. Figure 7 depicts the available ramp up and down flexibility for the VPP for a day. Here, it can be seen that for the strategy with no forecasting there is fast degradation of ramp up and down flexibility due to not knowing shiftable energy. This causes moments where the VPP is not longer able to meet the day ahead profile and thus generating imbalances.
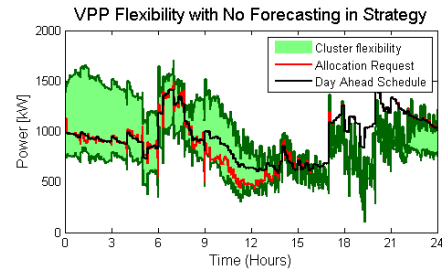


Fig. 7. Flexibility Degradation with No Forecasting.

However, in Figure 8, the same day using a forecasted ramp up and down capacity, the degradation is clearly preserved allowing the VPP to maintain its day ahead schedule when imbalance prices are lower as well as avoiding generating imbalances. This was seen to an even further degree for the perfect forecast strategy.
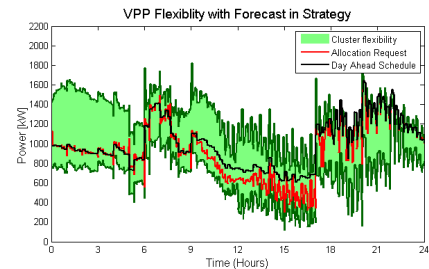


Fig. 8. Flexibility Degradation with Machine Learning

A comparison between total power allocation for each control strategies to the settled imbalance price can be seen in Figure 9. Here it can be seen that the no forecast strategy offers more ramp down flexibility at hour 9-12 when imbalance prices are high however it is at the expense of generating large imbalances in the evening (hour 18-24). Perfect forecast and

machine learned forecasted strategies are almost identical by offering less flexibility but maintaining balance in the evening.
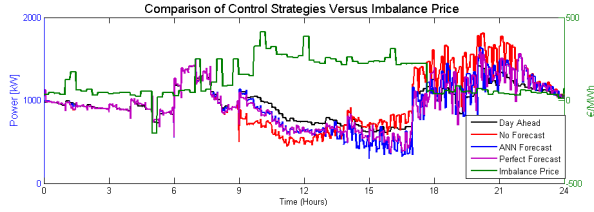


Fig. 9. All Control Strategies Allocations Versus the Imbalance Price

An overview of the economic evaluation of all strategies can be seen in Table III. Using the APX prices it is calculated that the total cost for 1000 households on the day ahead market was € 16,773 for one month. The cost is the settled price the VPP must pay for generating imbalances. Here it can be seen that with black box forecasting alone an 82% reduction in cost was seen. Further the perfect forecast reduced costs from generated imbalances by 86%. Additionally, the revenues from trading ramp and down flexibility were significantly increased for both the machine learned and perfect forecast control strategies. Finally, if treating the no forecast and perfect forecast as the upper and lower bound the simple black box machine learned technique reaches 89% of the achievable profit benefit. It should be noted that in addition to knowledge of the available flexibility, profit is dependent on the imbalance prices for the day. For the no forecast and forecasted case, the previous day minimum and maximum imbalance prices were used as an overall upper and lower bound for cost assignment of flexibility. With the exception of a few days, the daily minimum and maximum imbalances prices were similar. Further, on the days where the previous days imbalance prices were quite different, there was also limited flexibility available for balancing services due to a shift in outdoor temperature.

TABLE III
COST PROFIT EVALUATION OF VPP.

|  | No Forecast | Forecasted Capacity | Perfect Forecast |
|---|---|---|---|
| Cost (€) | 1,427 | 257 | 199 |
| Revenue (€) | 1,273 | 3,482 | 3,664 |
| Profit (€) | -154 | 3,224 | 3,465 |

It should be noted that the VPP did not offer flexibility when a revenue could not be made. However, cost reductions specifically in the day ahead costs could be also potentially be significantly reduced if flexibility forecasting was incorporated in the day ahead profile generation. Here some flexibility could be reserved to purchase energy when the imbalance price is lower than that of the day ahead market.

## VIII. CONCLUSION

Black box machine learning of flexibility capacity of a heterogeneous cluster can be done with a high accuracy of <5%. This top down approach allows shiftable electricity to be estimated without communicating large amounts of data or requiring end users to share privacy sensitive information outside the home. This knowledge also lowers imbalance risk for aggregators when using VPP flexibility for smart grid services. It was shown that applying models to multi-market trade, a VPP of residential demand response can be profitable without jeopardizing stability of the network, i.e. generating large imbalances and thus cost. In fact, imbalances were absorbed resulting in significant profitable trade on the imbalance markets. Specifically, it was seen that up to 89% of gain is possible by using black box supervised forecasting compared to a perfect forecast, using known flexibility capacity and imbalance prices. When combining the gain with the cost from day ahead trade, the overall monthly cost of electricity for the VPP decreased by 20%. Flexibility characterization is necessary for low risk operation of smart grid services. This can be accurately forecasted with black box approach machine learning models. Incorporating such a prediction model into the business logic of an aggregator increases optimal trade strategy.

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