Analysis of Smart Grid Balancing using Realistic Customer Models

Konstantina Valogianni[1,*], Wolfgang Ketter[1], Mathijs de Weerdt[2], and John Collins[3]

[1]Rotterdam School of Management, Erasmus University, Netherlands

[2]Delft University of Technology, Delft, The Netherlands

[3]Dept of CSE, University of Minnesota, Minneapolis, MN

[*]Student Author

Abstract

The decentralized and deregulated design of the Smart Grid necessitates a new approach to the grid balancing problem. In this paper we implement dynamic residential customer models validated by real-world data, and impose a balancing mechanism that uses load shifting to reduce the need to adjust power production through top-down control. Furthermore, we show that our proposed mechanism is scalable to thousands of customers. Finally, we explore the interaction between retail energy brokers and their customers and examine the extent to which truthful declaration of the cost of curtailment can influence the profitability of brokers. The a priori determination of the relationship between cost declaration and profitability is a complex machine learning problem for the broker. Thus, being able to know in advance what impact the specific deviation will have, is crucial for designing broker decision strategies.

1 Introduction

A number of factors are converging to fundamentally change the structure of energy markets, including the increasing prices and environmental degradation associated with fossil fuels and nuclear energy, the increasing availability of renewable energy sources such as wind and solar, and the expected transition to electric vehicles. One response to these pressures is the ongoing transition from regulated monopolies to liberalized markets in the electricity sector, but the 2000-2001 crisis in the California energy market [4, 3] shows what can go wrong when poorly designed markets are introduced without adequate analysis. Another is the various "smart grid" initiatives [1], including "smart" meters that can support dynamic pricing, and demand-side management technology that can remotely manage loads in individual households and businesses. Market liberalization at both wholesale and retail levels is also an important element, because it allows for innovations that cannot realistically arise in a regulated monopoly environment, and, at least in theory, should do a better job of allocating the output of variable-output renewable power sources to customers.

Two features distinguish retail electricity markets from most other types of markets: (1) the need for continuous balance between supply and demand, and (2) the fact that all players share the distribution infrastructure, and electricity is a pure commodity product. The result is that without an effective mechanism design for balancing, individual retail brokers can "free ride" by selling power without having purchased an equal amount of power. This problem is relatively easy to solve in an environment where virtually all power is produced centrally by baseload facilities such as hydro and fossil fuel plants, and where the retail customers are almost exclusively consumers, and not producers of power [16]. The problem becomes much more complex as the proportion of variable-output renewable sources increases, and as distributed production and storage facilities are introduced into the retail grid.

The liberalization of energy markets is expected to lead to the appearance of many retail energy providers, *brokers*, that have an active role in the energy transactions [2]. Their main goal is to maximize profit, by offering appealing energy tariffs to prospective customers to build a robust customer portfolio, and supplying them by purchasing power in the wholesale market. The Power Trading Agent Competition[1] [12] is a realistic competitive simulation that allows brokers with various trading strategies to compete in a market environment equipped with smart meters, basic demand-side management capabilities, and a variety of baseload and renewable energy sources. Thus, this simulation environment is of special interest to study the design and application of balancing mechanisms.

In previous work, we have developed a mechanism for market-based balancing [6] and shown that it has desirable properties, such as incentive compatibility with respect to the cost for brokers to exercise the demand-side management capacities of their customers. Because these results are only theoretical, it is important to evaluate the proposed balancing mechanism in realistic conditions. Reliable results depend on realistic customer modeling. Additionally, the scalability of the balancing algorithm needs to be evaluated in a realistic context, to prove that could be applicable in the real energy grid.

We study the balancing problem in the liberalized energy market in the light of the optimal payment allocation in each point of time, making use of demand-side management or *controllable capacities* (such as thermal storage facilities) embedded in the customer models. Our main objective is to test the incentive compatibility and the scalability of the proposed balancing mechanism in an energy market with customers owning controllable capacities.

This paper is organized as follows. In Section 2 we provide the description of the simulation environment that serves as a validation testbed for our mechanism. In Section 3 we describe the customer modeling approach followed to create realistic customers and in Section 4 the proposed algorithm is tested with respect to scalability and truthfulness. In Section 5 is presented a review of related literature. We conclude this paper with further extensions related to both the customer modeling and the balancing mechanism.

[1] http://www.powertac.org

2 Simulation environment

The simulation environment [12] provides a realistic representation of a retail *tariff market* for electric power. The tariff market allows brokers to publish tariffs for selling or buying energy and attract both consumers and producers. Within this context, the involved parties *consumers*, *producers*, and *brokers* act selfishly in order to maximize their profit or utility through transactions in this market. An ideal portfolio of tariff customers will tend to consume power when it is inexpensive on the wholesale market, and produce power at times when wholesale prices are high. Any imbalance is resolved by the *Distribution Utility, (DU)*, which is typically a regulated monopoly that owns and operates the distribution infrastructure and is ultimately responsible for balancing its grid. We assume predefined time intervals for the simulation (*timeslots*), $t \in [0, 95]$, which represent 15 min of real time. So, a day is being represented by $24 \cdot 4$ timeslots.

The DU has two available technical mechanisms to achieve balance: (1) it may purchase or sell power through the wholesale "regulating" or "ancillary services" market, or (2) it may exercise contracted *controllable capacities* [17] that are offered by individual brokers. Controllable capacities are those that can be regulated "upwards" or "downwards" to consume overproduced energy or reduce overconsumption, for balancing purposes. Household examples include water heaters, heat pumps or CHPs that can be remotely manipulated for regulatory actions. Other controllable capacities may be dishwashers or washing machines that are pre-loaded and their starting timeslot is chosen according to the balancing needs of the DU.

2.1 Customers

The customers are composed by different types of household customers varying from employees, students to retired persons, children, shift workers, unemployed etc., represented accordingly in the simulation environment. Each household is equipped with a set of household appliances and the persons living in this household perform various domestic activities, using household appliances. People may live in single apartments or family houses. Consequently, for each consumer $n \in N$, a specific energy demand $d_{n,t}$ is calculated for every timeslot t, derived by the activities performed in the household during this specific timeslot, as described in details in Section 3. Additionally, each household has a predefined maximum amount of *controllable capacities.* This amount includes capacities that can be manipulated by the DU in order to cover any potential overproduction or reduce any potential overconsumption. More specifically, on the customers's side domestic appliances such as the dishwasher, the washing machine, the heating pump etc are some of the controllable capacities available for balancing.

The customers interact in the tariff market with the brokers, and their *controllable capacities* become part of their portfolio. More specifically, the brokers are publishing energy tariffs to attract customers, cover their energy demand and make profit through these transactions. The customers that are contracted to a specific broker, compose the broker's total demand, as an aggregation of all the particular demanded amounts of energy, $\sum_{n \in B_j} d_{n,t}$. Furthermore, the aggregation of each customer's controllable capacities comprise the broker's total controllable capacities that can be regulated either downwards in order to balance potential overproduction or upwards to balance overconsumption. We denote those controllable capacities C_j^- for each broker B_j and symbolically assume that it has negative values, $C_j^- \in (-\infty, 0)$ for downwards regulation. Respectively, the broker's total controllable capacities for upwards regulation (in other words reduce consumption) are symbolically denoted as $C_j^+ \in (0, +\infty)$.

2.2 Producers

Large-scale producers are the Generation Companies, *GenCos*, attempting to supply the energy market with the amount needed in order to prevent any shortage periods. Specifically, they are producing for each timeslot, t, amounts of energy $G_{k,t}$ which vary among the different

GenCos, $k \in N$. They interact with brokers, in respond to their tariff offers, so as to benefit from being part of their portfolio. The brokers's objective is to attract as many producers as they need both to make profit and maintain a balanced portfolio. To this end, the aggregation of the contracted *GenCos'* production composes the broker's total production, $\sum_{k \in B_j} G_{k,t}$. This production for each *GenCo* is considered constant with no variation over the timeslots. This choice is supporting our main purpose, which is the thorough investigation of customer's demand and use of controllable capacities to the balancing direction.

2.3 Brokers

The brokers B_j, act as intermediary parties in the energy market having transactions with both consumers and producers. Their aim is to make profit through those transaction, maintaining at the same time a balanced portfolio. More specifically, for each timeslot t, the net imbalance for each broker B_j is:

$$x_{tj} = \sum_{k \in B_j} G_{k,t} - \sum_{n \in B_j} d_{n,t} \tag{1}$$

and can be positive $x_{tj} > 0$, *overproduction* and negative $x_{tj} < 0$, *overconsumption*. The brokers have to declare this net imbalance to the DU. An example of broker's total contracted supply and demand is presented in Fig. 1 (the generated demand and supply curves come from the customer models described in section 3). The distance between the two curves in each timeslot represents the broker's imbalance for the examined timeslot.

Additional feature of the brokers' portfolio is the controllable capacity that can be regulated either upwards or downwards, $c_j \in (C_j^-, C_j^+)$. This controllable capacity range is also reported to DU, in order to make use of the amount needed to balance demand and supply. In combination with their controllable capacities the brokers, declare costs for *upwards* regulation (production) and profits for *downwards* regulation (consumption). In the first case the DU pays to the brokers the cost for producing this extra capacity for balance's

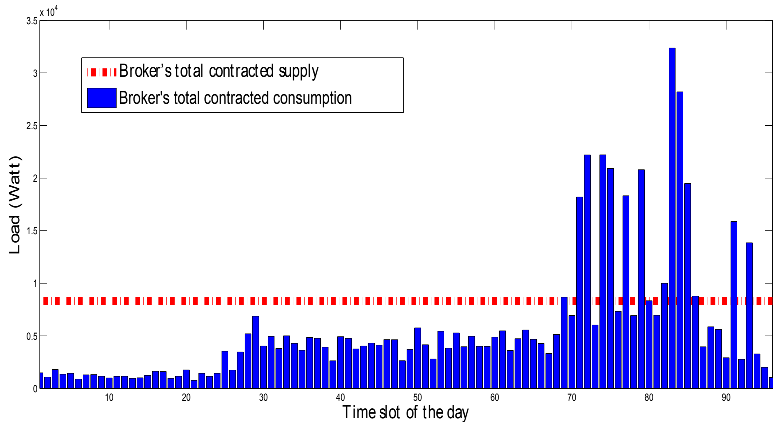

Figure 1: Broker's Contracted Supply and Demand for each time slot in a 24h horizon.

sake. In the second case the brokers pay the DU for the revenue they make for having their customers consume this extra energy amount. In both cases the main objective for DU is to minimize the payments (from the DU's side) which in the first case are negative and the second case are positive. More specifically, in each timeslot the broker declares the amount of controllable capacity that is willing to regulate upwards or downwards accompanied with the corresponding cost and revenue functions. The DU aggregates those declarations and makes use of the amounts that minimize both the cost payments (positive) and the profit payments (negative). In case of the cost and profit functions described below, the problem of the optimal payment allocation is a convex-optimization problem.

In the presented simulation the brokers use quadratic cumulative cost functions in order to determine the cost on the controllable capacity units. The quadratic cost function assumption is based on the fact that for each extra controllable capacity needed for the balancing, the broker needs to pay more to the corresponding customer, in order to make this unit available to the balancing mechanism. Thus, the quadratic function is a good approximation of this non-linear relationship between the controllable capacity units and the cost that the broker has to pay, to make them available for balancing. The general cost function form used in our approach is as follows:

$$cost_{up,j}(c_j) = a \cdot {c_j}^2 + b \cdot c_j + e \tag{2}$$

with $a > 0$ and $e > 0$ in order to have monotonically increasing marginal cost and to satisfy the constraint that for $c_j \sim 0$ we have $cost_{up,j}(c_j) \geq 0$. The graph in Fig. 2 depicts a variety of cumulative cost functions corresponding to the brokers in the market. We choose a starting cost for the controllable capacity, so we must always have $e \neq 0$. As far as the cumulative revenue function is concerned, the brokers have functions of the following form:

$$revenue_{down,j}(c_j) = g \cdot \sqrt[3]{c_j - d} \tag{3}$$

with $g > 0$ and $d > 0$ in order to have monotonically decreasing marginal profit. The reason for this choice is described by the idea that no, the broker has t be paid by the customer for every extra controllable unit that the customer can consume (downwards regulation). Thus, for each extra unit, the customer has to pay less to the broker, since the broker needs this downward regulation to have a balanced portfolio, while the customer may not need to consume this extra unit. Common example is the case that the customer may turn his/her heating pump on for consuming the extra energy. With this revenue function, we assure both that the customer will consume only in the case that he/she needs to consume (otherwise, there is no reason to pay the broker), and at the same time the broker, has his portfolio surplus consumed, avoiding the high imbalance penalties by the DU. The graph in Fig. 3 depicts a variety of cumulative revenue functions corresponding to the brokers in the market. The revenues are denotes with negative values, since those revenue amounts need to be paid by the broker to the DU.

2.4 Distribution Utility

The Distribution Utility acts as a market operator that is responsible for maintaining the balance between the trends of demand and supply. On every timeslot, the brokers report

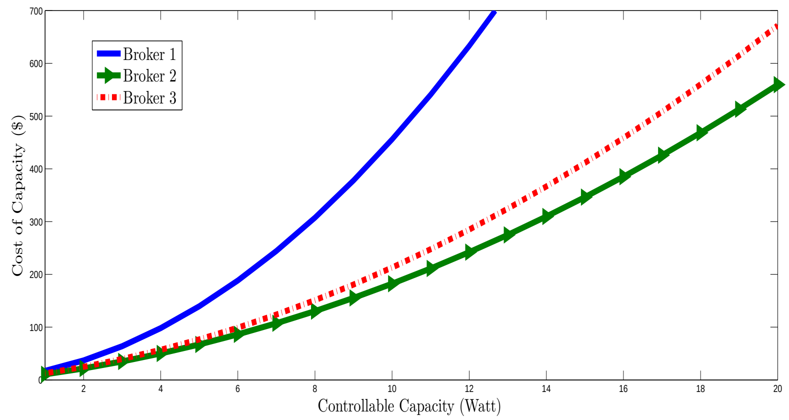

Figure 2: Cumulative cost functions for controllable capacities, upwards regulated.

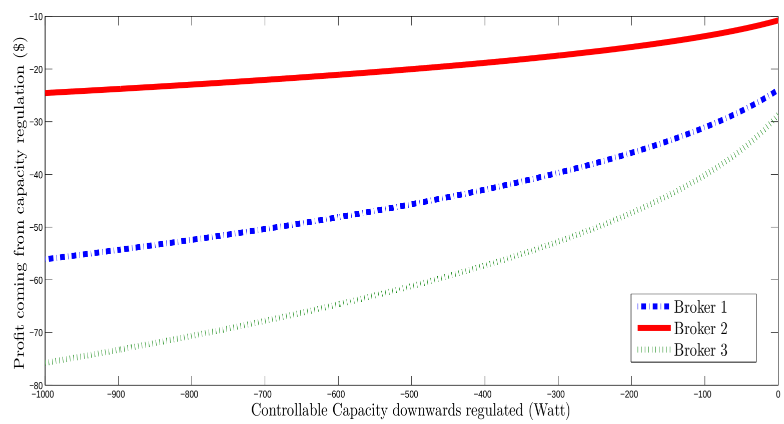

Figure 3: Cumulative revenue functions for controllable capacities, downwards regulated.

to the DU the net imbalance in their portfolio, x_{tj}. The DU in return imposes payments or rewards that correspond to controllable capacities used for the balancing procedure. This allocation must be optimal and provide credits to the brokers that participate. The payment allocation mechanism is described in Section 4.

3 Customer Modeling

3.1 Residential Model Description

A realistic customer model will provide accurate validation of the proposed balancing mechanism. Thus, we create implement various load profiles based on statistical data referring to the appliance availability, the residents' schedule, as well as appliances' consumption data over the day. The saturation data for each appliance determine the percentage of the population that have possession of each appliance. These data come from the "Bundesverband der Energie und Wasserwirtschaft (2009)" as presented in [8]. Fig. 4 depicts the modeling process as followed to create the individual customer models. The creation of each individual customer is a highly dynamic process, as each household is created in a stochastic way with various features and activities interdependencies. In Fig. 5 are presented the appliances included and the respective saturation.

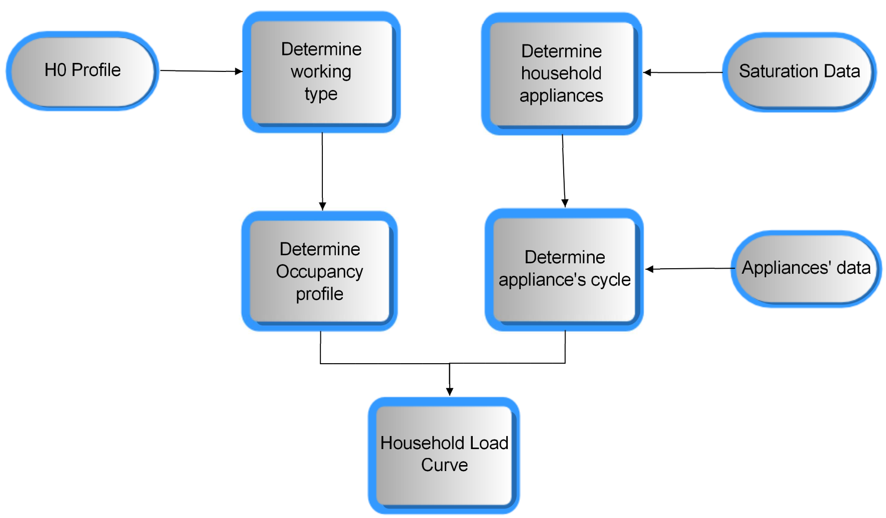

Figure 4: Residential load curve creation.

Having specified the appliance-set available in each household, the occupancy profile should be defined. In order to specify the occupancy of each household we assume the H_0 profile as presented in [8]. According to H_0 profile the population is divided to working people, students, etc. who are present in the household during pre-specified periods before

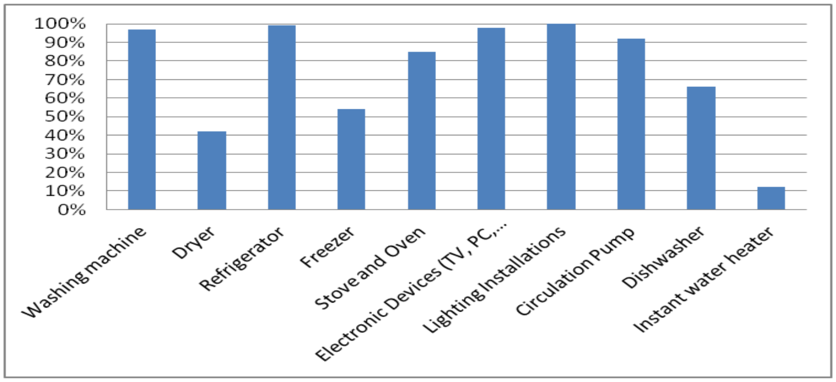

Figure 5: Appliance saturation (source H_0 profile).

Table 1: H_0 profile and the share of each group.

Working type	Share (%)	Start work (hour of the day)	Absence for work (hours)
worker, student	53	[7 – 8.30]	8
unemployed, retired	40	-	-
shift worker	7	random	8

or after their absence for working activities, to retired, unemployed, etc. who are mostly present in the household and shift-workers who are absent from household during unspecified periods over the day. Table 1 is presenting the share of each group in the whole population. For the working people we assume that they start working in the interval [7 – 8.30], work for 8 hours and return to their domestic activities during the interval [17 – 18.30]. The unemployed/retired people are assumed to wake up in the morning in the same interval [7 – 8.30] and spend most of their time in domestic activities.

In order to create the residential load curve corresponding to each household, the appliances functionality has to be divided into cycles lasting one timeslot (15 mins) and the starting points of the different activities to be allocated according to the customer's presence or absence. At this point a logical sequence of activities is followed and the different level of activities dependencies is determined based on the people's occupancy. During customer's absence or over night we assume consumption from appliances that function independently from human's presence (i.e washing machine that has been loaded by the resident, chargers and other electronic devices) and standby consumption from the appliances available in each

Table 2: Appliances data referring to the power consumption and stand-by consumption, total functionality duration and daily probability of occurrence. Data for power consumption and cycles [8], for standby consumption [15], and probability of occurrence [13].

Appliance	Consumption (W)	Stand-by Consumpt.(W)	Duration (min)	Probability of Occurrence
Washing machine	600	6	105	0.32
Dryer	1410	2.2	105	0.29
Refrigerator	140	1.7	15	1
Freezer	106	1.7	15	1
Stove and Oven	1840	2.2	30	0.585
Electronic Devices	150	67	90	1
Lighting Installations	350	0	120	1
Circulation Pump	90	2.2	975	0.3
Dishwasher	530	1.3	135	1
Instantaneous water heater	12000	0	15	0.3

household. The data used for each appliance are depicted in Table 2.

In order to determine the starting point of each activity including specific appliances, we take into account the probabilities of occurrence in a day [13] as presented in Table 2. Those probabilities are calculated as a weighted average from the probabilities of occurrence during the weekdays and the weekends. For the electronic devices the average of all those devices' probabilities is used (TV, PC, stereo etc.). Consequently, according to the probability of occurrence, the saturation and the working type of each customer we create individual load profiles, which vary on the appliances available, the working hours etc. The presented model is highly dynamic as it includes all kind of activities in a regular household and takes into account the interdependencies between them. Additionally, depending on the number of customers residing in a specific household, the consumption varies as there may be overlap in each person's activities. Using the current model, we are able to simulate large populations of residential customers, including all the particular residential consumption characteristics.

3.1.1 Customer modeling verification

The proposed model is being tested against real-world data in order to confirm its accuracy. The data available are household consumption measurements referring to time slots of 15 minutes for a week's time horizon and are obtained in cooperation with European Distribution Utility. They are coming from 24 households in the Netherlands and they are used to generate an aggregated profile which is tested against the generated profile from our model. Those data are consumption measurements, obtained before any balancing actions. The second profile is generated for 24 load curves picked randomly from our simulation. Those 24 load curves are aggregating data from consumption over a week's horizon. The comparison in the two profiles is presented in the Fig. 6. We use Pearson's coefficient $r = 83\%$ as a goodness of fit for the two curves [?]. This means that the aggregation of 24 weekly load curves is 83% correlated with the respective aggregation of 24 weekly load curves picked randomly from the real consumption data, which indicates a very high fit.

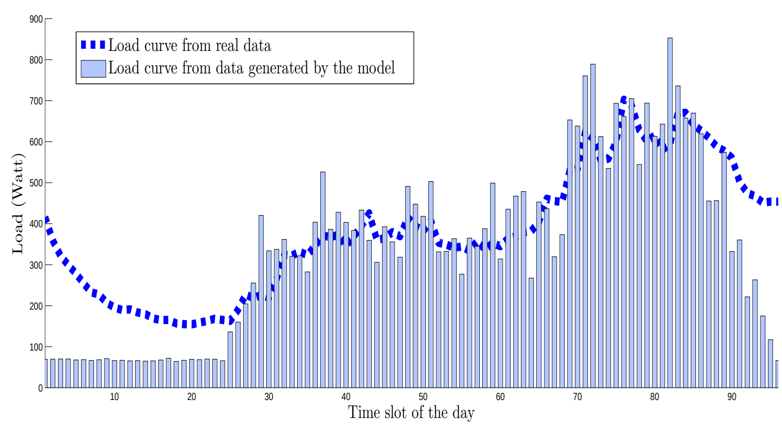

Figure 6: Generated load curve against load curve from real data.

4 Validation of the Balancing Algorithm

Within the context of the simulation environment presented in Section 2 we validate the balancing mechanism proposed in [6]. More specifically in this balancing mechanism the

VCG [6] payment allocation is used, where each broker pays "opportunity cost" that its presence introduces to all the other brokers. If the assumption of no real-time matching of the brokers' imbalances holds (the brokers are not allowed to counterbalance each other's imbalance), the DU is responsible for making use of the controllable capacities available in each broker's portfolio to achieve the optimal combination in order to have minimal cost. According to the VCG mechanism (defined on the minimal cost and not on the maximum well fare) the payments to or from i^th broker in the simulation are:

$$p_i(\delta) = -\sum_{j \neq i} \delta_j^{-i} \cdot cost_j(\delta_j^{-i}) + \sum_{j \neq i} \delta_j^{-i} \cdot cost_j(\delta_j^{i}) \tag{4}$$

where δ is the vector with the optimal capacity allocation and δ_j^{-i} is the vector with the optimal capacity allocation if we exclude the i^{th} broker, i.e. the controllable capacity for this broker is considered 0. For extended proof and explanation of the mechanism see [6, 12]. The cost function for the corresponding controllable capacities is denoted by $cost_j(\cdot)$. If x_i each broker's imbalance, we have $\sum_{i \in N} x_i < 0$ in case of over consumption and $\sum_{i \in N} x_i > 0$ for over production. In the first case, the controllable capacities (CC) for upward regulation are used ($CC > 0$) and in the second case the controllable capacities for downward regulation are used ($CC < 0$). In both cases, if we assume cost and revenue functions as described in Section 2.3, the problem of defining the optimal capacity and payment allocation is a convex optimization problem [5] and can be solved by various available methods (eg. interior-point methods etc).

The proposed balancing mechanism applies load shifting in the sense that in order to resolve the imbalances in the current timeslot, the loads controlled, are shifted to the next timeslot. Thus, the Demand Side Management (DSM) technique used, avoids avalanche effects that occur from long term load shifting or postponing.

Consider the optimal payment allocation as presented in Table 3. In this scenario we have a total imbalance $\sum_{i \in N} x_i = -9.6 \cdot 10^4$ (overconsumption), so the controllable capacities for

Table 3: Payment allocation for the controllable capacities according to VCG mechanism

Broker	Surplus (W)	Control. Capacity(W)	Cost ($)	p_i ($)	Capacity Used (W)
1	$-1.24 \cdot 10^4$	$4.76 \cdot 10^4$	$3.62x_1^2 + 8.86x_1 + 4.69$	$-0.36 \cdot 10^9$	$0.69 \cdot 10^4$
2	$-2.01 \cdot 10^4$	$8.98 \cdot 10^4$	$0.98x_2^2 + 8.28x_2 + 1.29$	$-1.51 \cdot 10^9$	$2.55 \cdot 10^4$
3	$-1.81 \cdot 10^4$	$5.11 \cdot 10^4$	$1.24x_3^2 + 8.60x_3 + 2.64$	$-1.14 \cdot 10^9$	$2.02 \cdot 10^4$
4	$-3.43 \cdot 10^4$	$4.27 \cdot 10^4$	$5.84x_4^2 + 0.22x_4 + 0.05$	$-0.22 \cdot 10^9$	$0.43 \cdot 10^4$
5	$-1.17 \cdot 10^4$	$6.64 \cdot 10^4$	$0.63x_5^2 + 1.46x_5 + 0.61$	$-2.69 \cdot 10^9$	$3.97 \cdot 10^4$

upward regulation are used. Here we assume 5 brokers in the simulation and 50 consumers and 50 producers. Each broker's portfolio imbalance is depicted in the column *Surplus*. Further, each broker's controllable capacity for upward regulation is presented in the column *Control. Capacity*. For each broker, the cost function for the controllable capacity is defined in the column *Cost*. We assume the cost functions $cost(c_i) = a \cdot c_i^2 + b \cdot c_i + e$ satisfying the constraints presented in Section 2.3. With $c_{i,max}$ is denoted the controllable capacity that each broker makes available to the DU for balancing and x the total imbalance in the market for the current timeslot. In order to calculate the optimal vector δ with the capacity allocation, we conclude to the minimization problem:

$$\begin{aligned} &\textit{minimize} && \textstyle\sum_{i \in N} cost(c_i) \\ &\textit{subject to} && 0 < x_i < c_{i,max} \\ &\textit{and} && \textstyle\sum_{i \in N} x_i = x \end{aligned} \tag{5}$$

which is a quadratic optimization problem. N is the number of the brokers in the market. In the case that the cost functions on the broker's side are in the form described in Section 2.3, the problem is convex and various approaches can be used in order to reach to a solution (interior-point etc.).

4.1 Scalability Analysis

A crucial factor for the applicability of the balancing algorithm is the *scalability*. Under the assumption that the cost and profit functions, on the broker's side, have the form described in Section 2.3, the optimization problem for the payment allocation is convex [5?]. In Fig. 7 the runtime of our algorithm is presented in relation to the number of customers in the simulation. For simplicity's sake, but without loss of generality, we assume equal number of producers and consumers in the energy market ([1-500] consumers, [1-500] producers). The brokers in this experiment are varying in the range of [1-15]. The presented runtime for every number of customers includes the time needed for calculating the customer's consumption at the examined timeslot, the time needed for defining the optimal capacity combination and the runtime spent for payment allocation. The increase of the customers does not lead to a strictly linear increase of the runtime, since for each group of customers the appliances, the persons, the schedules vary. As a result, the controllable capacities are different. This leads to different optimization problems for every number of customers (consumers and producers), which are differentiated on the runtime for defining the optimal solution. Another factor which affects the runtime is that the optimization differs in case of surplus or shortage. In case of surplus the DU makes use of the controllable capacities regulated downwards and minimizes the payments over the function $revenue_{down,j}(c_j) = g \cdot \sqrt[3]{c_j - d}$ while in case of shortage the upwards regulated controllable capacities are used and the optimization problem is referring to quadratic functions $cost_{up,j}(c_j) = a \cdot {c_j}^2 + b \cdot c_j + e$. In Fig. 7 we present the runtime as function of the number of customers as well as the respective standard deviation. On the X axis there are the groups of customers such as 1 corresponds to $[0-100]$ customers, 2 to $[101-200]$ etc.

The size of the error bar is indicating the variability of the runtime depending on the number of brokers in the market and at the same time the stochastic nature of the model. The number of brokers are selected based on realistic criteria. In most of the existing European and US energy markets the maximum number of energy retailers [2] (brokers) is 6 [?]. So our assumptions about the brokers satisfies the realistic conditions.

[2]http://www.escosa.sa.gov.au/consumer-information/energy-retailers.aspx

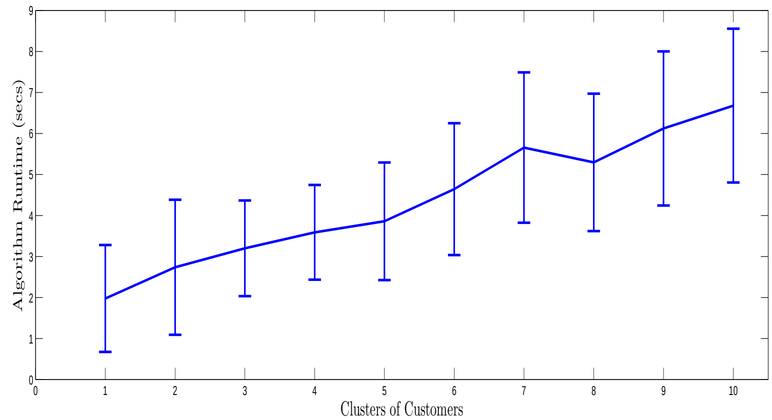

Figure 7: Runtime as a relation to the number of customers in the energy market, for different number of brokers [1-15]. The clusters of customers indicate customer grouping such as [0-100], [101-200],...[901-1000].

4.2 Degree of Truthfulness

The application of the VCG mechanism for the optimal payment allocation, provides incentives for ensuring the truthfulness with respect to the declaration of the cost and revenue function. Possible untruthful declaration from the broker's side in order to make larger profit, leads to profit reduction instead of increase.

In the following scenario we consider a simulation environment with 50 consumers and 50 producers and 3 brokers. Let the 3^{rd} broker be untruthful regarding the cost function (in this case profit) for regulating upwards the controllable capacity available in the broker's portfolio. All the other settings and parameters remain constant during this scenario (i.e the consumption, the production, each broker's imbalance and the profit functions of the rest of the brokers remain unchanged). The truthfulness of the broker's profit function is indicated as a percentage on the real profit function. The net imbalance in the market for the examined timeslot is $\sum_{i \epsilon N} x_i = 657.94$ so the controllable capacities for downwards regulation will be used. More specifically, the real data related to this example and the data influenced by the untruthful declaration are depicted on the Table 4. It is observed that even when the broker declares "double" cost as the actual cost, the profit is less than in

Table 4: Payment allocation to the controllable capacities according to VCG mechanism, with and without being affected by untruthful declaration from the 3^{rd} broker.

Broker	Revenue function($\$/W$)	p_i ($)	Revenue ($)	Profit function($)	p_i ($)	Profit ($)
1	$6.03 \cdot \sqrt[3]{x_1 - 105}$	10.79	28.25	$6.03 \cdot \sqrt[3]{x_1 - 105}$	9.88	22.69
2	$3.67 \cdot \sqrt[3]{x_2 - 57}$	5.68	12.67	$3.67 \cdot \sqrt[3]{x_2 - 57}$	4.90	10.41
3	$5.86 \cdot \sqrt[3]{x_3 - 26}$	6.71	26.95	$\mathbf{11.72} \cdot \sqrt[3]{x_3 - 26}$	19.95	**24.18**

case of truthful declaration. In Fig. 8 is presented the reduction of the profit against the fraction $untruthfulFunction/truthfulFunction$. As we can see the profit under untruthful declaration reaches the maximum value only at one point which is for truthful cost declaration. Additionally, the curve is not symmetric in the corresponding cases of equal reduction or increase in the percentage of the truthfulness. That is because the profit is given by the equation $profit = revenue - cost$. So the revenue and cost for the $3rd$ broker who is declaring "fake" function are changing with unequal rates and as a consequence their difference is modified accordingly. From this graph we derive the conclusion that if the broker decides to over-exercise the controllable capacities available ($untruthfulFunction/truthfulFunction > 1$), the reduction in the expected profit will not be as much the same as the reduction in the profit resulting from under-exercise ($untruthfulFunction/truthfulFunction < 1$). This result, is beneficial for the brokering strategies, since the a priori knowledge of the impact that the over-exercise or under-exercise may have on the cost, allows the broker to be more flexible in the decisions he is forced to make in real time. Each attempt from the broker's side to predict this impact, is a complex machine learning task that necessities accurate predictions [11]. Additionally, these prediction tasks may add computational load and the decision may not be feasible in the tight time constraints of the simulation environment. Finally, this result proves that there is significant loss for the individual that deviates from the truthful behavior, while theory only proves that there is no gain.

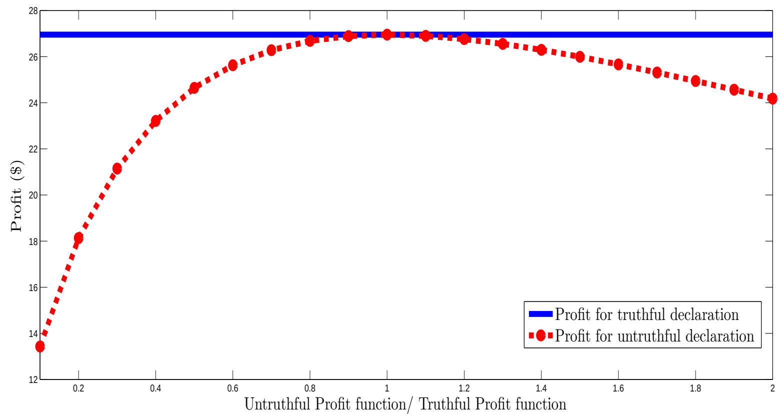

Figure 8: Profit for the $3rd$ broker according to degree of truthfulness.

5 Related Work

5.1 Residential Load Curve Simulation

Modeling the customer in high precision is key factor for an accurate balancing approach in the energy market. As the precise customer modeling, reduces the extent of uncertainty, allows for efficient balancing algorithms that are capable of preventing unlikely energy shortages. With respect to the modeling domestic load curves, various approaches have been proposed among the literature. The authors in [13] present a bottom-up modeling approach where saturation information for the domestic appliances are collected from households in Finland. They propose prioritization for the appliances, so as to achieve Demand Side Management (DSM) taking into account each device's priority. Nevertheless, no sophisticated DSM is applied in order to resolve imbalances. Furthermore, in [18] a stochastic approach based on Markov-chain models is proposed in order to create domestic load curves, but the authors do not model the appliances available in the household. They just define the occupancy profiles and based on them create the load curves. In [10] a method for generating domestic and Commercial & Industrial load curves based on consumption data collected from utilities in Sao Paolo, Brazil, is proposed. They perform statistical analysis to conclude to some representative load curves, as opposed to bottom-up approach that we use. The authors in [8] present a bottom-up household modeling approach and apply demand response programmes. They use stylized data to verify their results, whereas we use real-word data to evaluate the load curves with 83% degree of fit and made the model more dynamic in the sense of activities interdependencies and shifting to the next timeslot. Our proposed balancing approach constraints the load shifting up until the next timeslot, in order to prevent huge avalanche effects from continuous load shifting. Overall our modeling approach combines both appliance information and all the customer types from related works mentioned, so it is more complete and representative of the actual customer's behavior.

5.2 Balancing in the energy market

Balancing in the energy market is widely investigated, as to develop successful balancing strategies and eliminate imbalances between supply and demand. In [7] the authors assume that the balancing transactions take place only in the reserve market (following the German market prototype). The balancing has two steps: firstly reserve capacity is procured, and secondly in case of imbalance the balancing energy is delivered, based on the reserve capacity. According to that, only a two-part tariff could be efficient. The first part declaring the price for the capacity and the second part the price for the energy delivered. The authors in [9] propose a balancing mechanism based on bidding for reserve capacities. In their bids, generators include the opportunity cost of withholding reserve capacities. During the day-ahead auction the proposed mechanism operates as a one-shot auction, for which the System Operator collects bids for every hour of the next day. During the real-time phase for each hour of the following day, the balancing requirements are announced, and the System Operator computes an optimal allocation to settle the balancing demand. The authors in [14] consider three balancing elements. First the program responsibility where exist both producers and consumers and inform TenneT (system operator) about their demand and supply. Second the single-buyer market for regulation and third the reserve power where TenneT tries to resolve unexpected imbalances.

6 Conclusions and Future Work

The presented balancing approach is deployed within the context of Power Trading Agent Competition [12]. It resolves imbalances for the current timeslot, assuming the existence of controllable capacities on the customers' side.The proposed mechanism suggests load shifting for the next timeslot, since the capacity that regulated in the current timeslot, shows up in the next timeslot. We have implemented customer models using the bottom-up approach and evaluated them against real-world consumption data, obtaining a high degree of fit. We have validated the applicability of the proposed algorithm in practice and we have verified the scalability of the algorithm to thousands of customers that may differentiate on the consumption features. Finally, we proved that the proposed balancing mechanism provides incentives to the customers for truthful cost declaration. Every deviation from the truthful cost value, leads to profit reduction for the corresponding broker. Future extensions of the current work, is to model the customer in the device level and make use of higher resolution cost functions that will reflect the exact cost of each controllable capacity in particular (i.e. different cost for heat pump, Air Conditioning etc). An additional extension is to define the exact cost and profit functions reflecting the specific controllable capacities availability in the broker's portfolio for every timeslot. This will make the system more dynamic, as the functions will vary among the different timeslots as the broker's portfolio will be changing. With respect to the balancing approach, we are planning to extend the mechanism in resolving the imbalances across timeslots. Finally, we will extend the customer models both to creating the producer models and to embedding in the consumer production features (such as PEVs, photovoltaics etc).

References

[1] Massoud Amin and Bruce Wollenberg. Toward a smart grid: Power delivery for the 21st century. *IEEE Power & Energy Magazine*, 3(5):34–41, 2005.

[2] Martin Bichler, Alok Gupta, and Wolfgang Ketter. Designing smart markets. *Information Systems Research*, 21(4):688–699, 2010.

[3] Severin Borenstein. The trouble with electricity markets: Understanding California's restructuring disaster. *Journal of Economic Perspectives*, 16(1):191–211, 2002.

[4] Severin Borenstein, James B. Bushnell, and Frank A. Wolak. Measuring market inefficiencies in California's restructured wholesale electricity market. *The American Economic Review*, 92(5):1376–1405, 2002.

[5] S. P. Boyd and L. Vandenberghe. *Convex optimization*. Cambridge University Press, 2004.

[6] Mathijs de Weerdt, Wolfgang Ketter, and John Collins. A theoretical analysis of pricing mechanisms and broker's decisions for real-time balancing in sustainable regional electricity markets. In *Conference on Information Systems and Technology*, pages 1–17, Charlotte, November 2011.

[7] Kai Flinkerbusch. A more efficient procurement mechanism for reserve capacity in the german market for balancing power. CAWM Discussion Papers 52, Center of Applied Economic Research Mï¿œnster (CAWM), University of Mï¿œnster, 2011.

[8] Sebastian Gottwalt, Wolfgang Ketter, Carsten Block, John Collins, and Christof Weinhardt. Demand side management - a simulation of household behavior under variable prices. *Energy Policy*, 39:8163–8174, 2011.

[9] Nicolas Höning, Han Noot, and Han La Poutré. Integrating power and reserve trade in electricity networks. In *AAMAS '11: Proceedings of the tenth international joint conference on Autonomous Agents and Multiagent Systems*, 2011.

[10] J.A. Jardini, C.M.V. Tahan, MR Gouvea, S.U. Ahn, and FM Figueiredo. Daily load pro-

files for residential, commercial and industrial low voltage consumers. *Power Delivery, IEEE Transactions on*, 15(1):375–380, 2000.

[11] Wolfgang Ketter, John Collins, Maria Gini, Alok Gupta, and Paul Schrater. Detecting and forecasting economic regimes in multi-agent automated exchanges. *Decision Support Systems*, 47(4):307–318, 2009.

[12] Wolfgang Ketter, John Collins, Prashant Reddy, Christoph Flath, and Mathijs de Weerdt. The power trading agent competition. Technical Report ERS-2011-027-LIS, RSM Erasmus University, Rotterdam, The Netherlands, 2011.

[13] J.V. Paatero and P.D. Lund. A model for generating household electricity load profiles. *International Journal of Energy Research*, 30(5):273–290, 2006.

[14] Van der Veen Reinier and De Vries Laurens. The impact of microgeneration upon the dutch balancing market. *Energy Policy*, 37(10):2788–2797, 2009.

[15] JP Ross and A. Meier. Whole-house measurements of standby power consumption, 2006.

[16] Klaus Skytte. The regulating power market on the Nordic power exchange Nord Pool: An econometric analysis. *Energy Economics*, 21(4):295–308, 1999.

[17] E. Sortomme and MA El-Sharkawi. Optimal power flow for a system of microgrids with controllable loads and battery storage. In *Power Systems Conference and Exposition, 2009. PSCE'09. IEEE/PES*, pages 1–5. IEEE, 2009.

[18] J. Widén and E. Wackelgard. A high-resolution stochastic model of domestic activity patterns and electricity demand. *Applied Energy*, 87(6):1880–1892, 2010.