The Impact of Smart Grid Prosumer Grouping on Forecasting Accuracy and its Benefits for Local Electricity Market Trading

Per Goncalves Da Silva, Dejan Ilić, and Stamatis Karnouskos

Abstract—**Local electricity markets may emerge as a mechanism for managing the increasing numbers of distributed generation resources. However, in order to be successful, these markets will heavily rely on accurate forecasts of consumption and/or production from its participants. This issue has not been widely researched in the context of such markets, and it presents a clear roadblock for wide market adoption as forecasting errors result in penalty and opportunity costs. Forecasting individual demand often leads to large errors. However, these errors can be reduced through the creation of groups, however small. In the work presented here, we investigate the relationship between group size and forecast accuracy, based on Seasonal-Naïve and Holt-Winters algorithms, and the effects forecasting errors have on trading in an intra-day local electricity market composed of consumers and "prosumers". Furthermore, we measure the performance of a group participating on the market, and demonstrate how it can be a mitigating strategy to enable even highly unpredictable individuals to reduce their costs, and participate more effectively in the market.**

Index Terms—**Smart Grids, demand forecasting, autonomous agents, renewable energy resources, energy management**

I. Introduction

THE smart grid [1] poses a paradigm change in the electricity domain that will empower a new generation of innovative applications and services. The increasing penetration of distributed renewable generation and the dynamic involvement of the envisioned stakeholders [2] will have a dramatic effect on the power grid [3]. In the smart grid era, traditionally passive consumers, such as households and small businesses, are being empowered to also become producers. As they are outfitted with generation capacity, such as roof-mounted solar photo-voltaic (PV) panels, they can take a more active role in the system. The locational, and sometimes intermittent, character of distributed generation will emphasize local energy management and require higher stakeholder engagement, such as through the creation of cooperatives, or "energy communities" [4], and local electricity markets [5].

Electricity markets are seen as the cornerstone of liberalized power systems, and in the smart grid era they can also be applied as a "soft management control" at local level. They provide an efficient mechanism for the allocation and pricing of the generation capacity used to meet power demand. Market models such as [6], [7], and the NOBEL market model [8] used in our evaluation, have been shown to be an effective method for the coordination of local consumption and production. Given the instantaneous transfer of generated power, electricity markets heavily rely on forecasting in order to help ensure the operational stability of the power system, which requires a near constant balance between demand and supply.

In a local and intraday electricity market such as NOBEL, forecasting accuracy plays a key role for success of participants and market itself. High forecasting accuracy can also enable the market to provide enough feedback to push consumers towards periods of high availability (i.e. low prices) and producers to periods of high demand (i.e. high prices), thus alleviating peak consumption, making better use of intermittent renewable generation, and leading to economically favorable outcomes to the participants. However, forecasting demand requirements for small highly-dynamic entities, such as single households, can lead to higher errors and consequently to the market-related penalty costs. This might be a potential barrier for economically feasible participation and realization of such markets. Although such aspects will depend on applicable business models, it is expected that forecast accuracy will still be highly beneficial for the majority of them.

An important property of markets, in general, is that they provide a common interface through which different types of participants can interact in a timely and well-informed manner. As such, a participant's internal management and composition (e.g. a single household, group of households or a fleet of electric vehicles) may be hidden from the market, and therefore many different solutions could be proposed to tackle the issue of forecasting accuracy. One possible solution could be aggregating certain participants into small virtual groups named Prosumer Virtual Power Plants (pVPPs) [2] based on some key characteristics (e.g. social, consumption, location). A "prosumer" is a consumer that has its own production capacity (e.g. PV panel). Such groups not only exhibit lower forecasting errors, as we will demonstrate, but can also potentially lower the risk of market participation for their members through the internal sharing of resources, costs and benefits. The latter enables even unpredictable stakeholders to participate effectively in the market, which due to the incurred costs would otherwise not be economically sound.

In this work, we investigate the positive impact of grouping on forecasting accuracy, and how it can be exploited for effective participation within the NOBEL local electricity market. The evaluation is carried out through a simulation of the market interactions of various prosumers, consumers, and groups. The simulation is based on smart metering data

All authors are for SAP Research, Vincenz-Prießnitz-Straße 1, D-76131 Karlsruhe, Germany, Contact Email: {per.goncalves.da.silva, dejan.ilic, stamatis.karnouskos}@sap.com

collected during the NOBEL field trial in the city of Alginet, Spain in 2012. Furthermore, the PV generation output is calculated from historical solar irradiation and weather data for the same area during the trial. The main thrust of this work is guided towards the following key contributions:

- We investigate the relationship between forecast accuracy and group size, and show that significant improvement can be eve seen for small group sizes.
- We quantify the effects of forecasting errors on local electricity trading under different levels of distributed generation penetration.
- We quantify and compare the behavior of a group on the market, with that of its members under an individual trading regimen.
- We demonstrate that by participating as a group, the participants can reduce their potential market-related penalty and opportunity costs.

The remainder of this paper is organized as follows: in Section II, we summarize current efforts in the local electricity market domain, and describe the NOBEL market. In Section III, we investigate the behavior of forecasting accuracy in function of group size and show how forecasting errors can be dramatically reduced, even for small groups. In Section IV-A, we outline our evaluation methodology, simulation environment, and data. In Section V, we evaluate the impact of forecasting errors on the market. In Section VI, we demonstrate how participants can benefit from improved forecast accuracy and resource sharing to reduce their potential market related risks and costs. Finally, we conclude the paper in Section VII.

II. Market Aspects

The current focus on renewable generation and demand-side flexibility has placed new electricity market models at the heart of major roadmaps for the smart grid [9], [10]. In this section, we outline fundamental market concepts, present current efforts in this domain, and compare them to the NOBEL market model. Many of the proposed electricity market models found in literature have followed the double-sided auction approach, that is, auction models with many buyers and many sellers that generally fall into two categories: continuous double auctions (CDA) or call auctions (CA).

The CDA is the basis for many financial markets, such as the New York Stock Exchange. In the CDA, the market is cleared continuously as new orders are submitted. The CDA mechanism offers a highly efficient and decentralized approach to resource allocation, where the allocation emerges from the continuous interaction between participants. Generally, every time an order is submitted to the market, a transaction will occur only if there is a price match between buy and sell orders. Any submitted order that is not matched is stored in a publicly viewable order book. By accessing this information, the participants can quickly adapt to sudden changes in supply and demand. These sudden changes are a prominent characteristic of future electric grids, especially in the light of renewable generation, electric vehicles, and demand-side management and/or response. However, it should be noted that protocols and clearing rules for CDAs can vary between models and their target applications. As a reference, a widely studied CDA model can be found in [11] and CDA-based models in the energy domain can be found in [12], [13].

In contrast, in a CA the market clears at discrete time intervals. While this can lead to an optimal allocation, it can also hamper participants' efforts to adapt to changing market conditions. As such, we concentrate our research on CDA-based models. However, some CA-based electricity market models have been proposed [3], [13], [14].

The NOBEL market [8] model is based on the European Power Exchange (EPEX) Intraday Market (www.eex.com). It is composed of a series of concurrent CDAs, called timeslots. Every timeslot represents an interval (e.g. 15 minutes) within a known horizon (e.g. next 24 hours) where participants can place their orders to buy or sell electricity. The sequence of timeslots offers a platform for continuous trading in a rolling horizon. Participants use the interval of each timeslot as a reference to place orders based on their consumption/production forecast. The timeslot clears continuously as the participants submit orders. Generally, a transaction occurs when two orders match in price, that is, the bid price is greater or equal to the offer price. The price is set to the incoming order price (i.e. the order that makes the market "move"), while the quantity traded will be equal to the minimum quantity between the matching orders. Unmatched and partially matched orders are stored in the public order book or the respective timeslot. Furthermore, the model includes other order attributes that are considered by the clearing mechanism. For instance, a market order could be submitted to accept any price, or an order could stipulate that its entire quantity needs to be met (if not entirely met, transaction will not occur). The efficiency of the NOBEL market was already evaluated in terms of the usage of its underlying available resources [8]. In this case, under simple trading behaviors, trading at random prices, a lower-bound of about 75% efficiency was determined. Furthermore, it has been demonstrated to be scalable [15].

The NOBEL market differentiates itself from other proposed models, e.g. [12], [13], in that it positions itself squarely at the distribution system, without considering any transmission system aspects. Furthermore, the NOBEL market promotes balance between the local resources and demand, as a cheaper alternative to the retailer contracted electricity. Hence, the market becomes a tool for indirect price-based management of demand/supply operating under dynamic conditions. To make some realistic assumptions about the operational aspects of such a market, we consider that a portion of the consumer demand can be serviced through the market, while the remainder can always be provided through the retailer. The latter is mandatory due to security of supply conditions, and acts as a backup solution if not all energy can be provided via the market-based channels. This also makes harder constraints, such as inelastic demand, unnecessary.

Additionally, while calculating generation costs can be straightforward (i.e. fuel costs and capacity factors can be easily estimated), calculating the buy prices might not be as easy. A household might not be too concerned with the micro-cost associations of, for instance, watching TV, using the computer, or any other household task. However, in this case, the retailer costs can be used as a basis for trading on the market. Any price below the retailer contract price will represent a saving. Of course, this entails that the generation costs in the market are below that of the retailer costs. This is not currently the case, but as distributed generation costs decrease, and retailer centralized costs increase, we assume it will be the case in the future. For these reasons, we choose the NOBEL market model in our evaluation.

To summarize, intra-day CDA-based markets allow participants to follow and take advantage of the market as it develops. While CDAs will not always lead to an optimal allocation, current research suggests they are highly efficient. The evaluation of these novel market mechanisms has generally focused on their efficiency at solving different allocation problems. Inadequate attention has been given to the negative effects forecasting errors can have on these markets and their participants' activities. Large forecasting errors can be a fundamental barrier for the successful realization and adoption of local markets, as these are envisioned in the smart grid era. As such, these effects need to be analyzed and understood. This is especially true in the case of small-scale individual traders, like households, that may take a more active role in the future electricity markets as standalone or as part of ad-hoc groups like the pVPPs [2].

III. Group-Forecasting Accuracy Behavior

We have assessed the effects of grouping on demand-forecasting errors based on smart-meter measurements collected in the NOBEL project trial [16]. The measurement sampling rate was at 15 minutes for each meter. The original data set was quality-screened in order to obtain a high number of smart-meters without faulty or missing measurements. The resulting had 1974 smart-meters with sufficient historical data to, in our demonstration case, predict demand behavior for Tuesday, 07-Jun-2011. In order to understand the impact of grouping on achieving a higher load forecast accuracy, groups of different sizes were created by randomly choosing smart-meters from the dataset. Using this approach, we measured the changes in forecast accuracy as a function of different group sizes.

The smart-metering data was aggregated into groups on equal timestamps to produce a single demand time-series. Different forecasting algorithms were then applied, and the resulting predicted values were compared with the actual values. To measure the resulting accuracy, the Mean Absolute Percentage Error (MAPE) was used, as it can be compared regardless of the magnitude of the measurements taken. For instance, commercial customers will have a higher demand than residential customers.

An experiment was executed 100 times for each group of size n. Each time, a different group was randomly generated, and had its MAPE measured under different forecasting algorithms. The first subinterval was $n = [1, 25]$, by incremental steps of 1 (or 25 different group sizes), second $n = [26, 50]$ by steps of 5, third $n = [51, 100]$ by steps of 10, and fourth $n = [101, 180]$ by steps of 20. Figure 1 depicts the average MAPE for one day ahead forecast of two forecasting methods

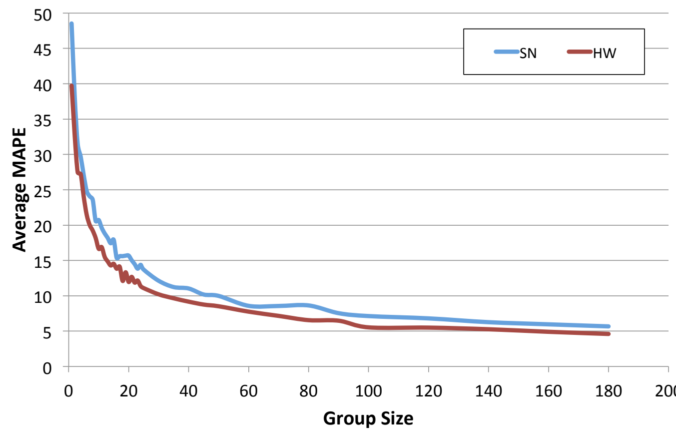

Figure 1. Grouping effect on the prediction accuracy (MAPE)

i.e. Holt-Winters (HW) [17] and Seasonal Naïve (SN) [18]. As can be seen, the forecast accuracy increased with group size, while in parallel the rate of improvement was decreased.

The results show that the simple forecasting method SN performs almost identically to the more advanced HW algorithm. This is interesting as the SN method, of one day season, uses identical values of a previous day interval to make the forecast, while 4 weeks of meter readings were used to train HW to forecast one day ahead. Nevertheless, HW showed a slightly better accuracy for all groups, concluding that the set resulted with an average MAPE of less than 5% already at the group size $n = 160$.

Improving forecasting accuracy through aggregation is nothing new for the electricity domain. For instance, [19] showed how prediction errors of wind power output are lower for a group of wind-farms than for a single site. However, here we demonstrate how rapid the forecast error reduces, even for relatively small groups, and how fast its point of convergence is reached. Next, we evaluate if this effect can be exploited to improve the trading outcomes of the market participants.

IV. Evaluation Methodology

A. Simulation Model and Data

The effects of grouping on the forecast error reduction are evaluated through a discrete simulation model of the NOBEL market in a similar setup to the one described in [15]. The simulation comprises 1897 participants trading on unique 15 minute intervals of the market for the month of September 2012. The participants are divided into two roles: consumers and prosumers. All participants have their own predicted electricity demand profile, while only the prosumers have generation capacity. The simulation advances 15 minutes per time-step, the duration of the market timeslots. At each time-step, the earliest timeslot is closed for trading, a new one is opened at the end of the sequence, and the participants submit orders to the market based on their forecasts. Data for each participant (e.g. real demand, predicted demand, quantity bought/sold) and for each timeslot (e.g. total consumption, total production, total energy traded) is collected for the evaluation.

The electricity consumption for each of the simulated participants is based on real smart-metering. These measurements, with a sampling resolution of 15 minutes and precision of 1kWh were taken during the NOBEL field trial, which took place in Spain at the end of 2012. These measurements are interpolated to produce the real demand profile of each participant. The SN forecasting algorithm is then applied to each smart meter individually, to produce the predicted demand for each participant. Although the HW algorithm displayed slightly better results, as depicted on Figure 1, we chose the SN algorithm for its simplicity and to form a baseline for future comparison.

The generation profile of the prosumers in the evaluation scenarios is simulated. The PV generation technology was chosen as it is a main player in the context of distributed generation, and due to its increasing growth in the residential and commercial rooftop segment [20]. Any participant with generation capacity is outfitted with a PV installation with an assumed efficiency of $\eta = 15\%$. The installation is sized so that it will produce up to 50% of the participants total demand for the simulated period. For instance, if a participant consumes 100 kWh within the simulated period, its PV installation would ideally produce 50 kWh over the same period, weather effects not withstanding. At this level, the average self-consumption rate over all prosumers will be roughly 70%, which was observed to be the saturation point of self-consumption for Spanish prosumers equipped with a photovoltaic system [21].

The solar radiation data used to simulate the participant's production is acquired from the European Commission's Joint Research Center's Photovoltaic Geographical Information System (re.jrc.ec.europa.eu/pvgis). The monthly radiation data is used to calculate the PV capacity of a participant, while the daily radiation data is used to calculate the 15 minute interval energy output (Wh) of the installation. The weather data is collected from the web-services offered by Wunderground (www.wunderground.com). Both irradiation and weather data are collected for the city of Alginet, in Spain, where the NOBEL trials took place. As an example, Figure 2 depicts the demand, predicted demand, and generation output of one day for one of the participants.

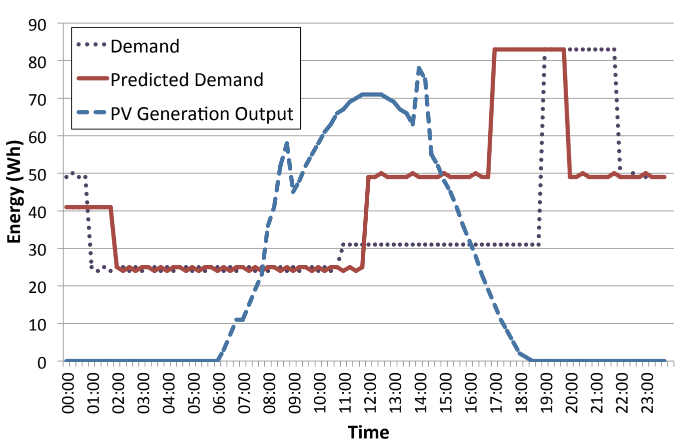

Figure 2. Example day of actual demand, predicted demand, and generation output for one of the participants.

For simplicity, no prediction errors are attributed to the production profile of the participants. As such, the amount of energy generated by a PV installation within an interval t is calculated as follows: $E(t) = \eta\alpha I_g(t)\omega(t)\tau$, where η is the efficiency of the installation, α is the area (m^2) of the installation, I_g is the global irradiation in a fixed plane (W/m^2), $0 \leq \omega(t) \leq 1$ is a dimensionless scaling factor in function of the weather conditions (e.g. clear sky is 1 while a thunder storm is 0), and τ is the timeslot duration in hours (0.25 in this case).

B. Trading Strategy

At each time-step, the participants trade on the earliest open timeslot based on their demand prediction, and generation output, if any. If the participant's forecast demand is greater than its generation output, it will attempt to buy the difference on the market. If the participant's generation output is greater than its forecast demand, it will attempt to sell the difference on the market. Thus, on any given timeslot, a participant is either a buyer or a seller. The underlying assumption in experiments is that the participants will try to consume their internal generation before going to the market. The participants will attempt to trade the entire calculated quantity. That is, they take no measures to reduce their errors by, for instance, trading only a portion of the calculated amount.

The Zero-Intelligence Plus trading strategy (ZIP) [22] is utilized by participants to simulate their market interactions. The ZIP trading strategy uses simple heuristics to adapt the participant's profit margin in response to market events: unmatched orders and transactions. The profit margin is calculated from the participant's limit prices for buying or selling. A limit price is the maximal (minimal) price a buyer (seller) will pay (offer). To simulate the continuous trading of the participants, within each time-step there are 1000 trading rounds. In a round, each active participants submits, or updates, an order. The new order will include the updated price, based on the recalculated profit margin, and any remaining quantity left to buy or sell. Once a participant has bought or sold its required quantity it becomes inactive and leaves the market. We have selected the ZIP for its simplicity and minimal complexity. However, no parameter tuning was carried out to improve the performance of the trading strategy. In this way, just as with the choice of prediction algorithm, a baseline can be established for future comparative assessment.

In our evaluation, all participants have a retailer contract of 14 c/kWh (as this is used in the NOBEL). This value defines the limit price for buyers in the market. An assumed production cost of 5 c/kWh is attributed to the PV installations of the prosumers, which sets their limit price for sellers. Since PV production costs are still more expensive than retailer costs, an assumed cost was chosen such that meaningful trading could be realized on the market. In our evaluation, we focus on the amounts of energy that can be attributed to penalty and opportunity costs, and defer economic analysis for future work. As such, the assumed costs are not critical to our evaluation. Our only requirement is that there be enough market activity to properly measure the effects of forecasting errors on the market. Furthermore, while the marginal cost of PV production is 0, we assume a positive, non-zero, cost to reflect the investment costs of the installation. Should the market prices fall bellow the limit price of the producers, it may be feasible that they would still sell into the market. However, in this evaluation, a simple, general purpose, trading mechanism is assumed. In the future, more advanced, and specifically tailored, trading mechanisms can be explored.

C. Evaluation Measurements

The evaluation is carried out in two parts. In the first part, the effects of forecasting errors on the market are evaluated under varying levels of PV penetration. In this case, all participants trade individually. This is done by comparing two scenarios, one in which all participants have no forecasting errors, and one in which they do. In the second part, the outcomes of group participation are evaluated. This is done by creating a group of participants that trade on the forecast aggregate behavior of its members. We then compare the performance of the group against the individual performance of its members. In both parts, the evaluation is centered on four key measurements: demand imbalance, uncapitalized generation, unnecessary buys and sells. If every participant p acting on a timeslot t has a (actual) consumption $C_{p,t}$, (actual) production $P_{p,t}$, amount bought from the market $B_{p,t}$, and amount sold to the market $S_{p,t}$, these measurements are defined as follows:

Definition 1: A participant can have a *Demand Imbalance* $\delta_{p,t}$ on a timeslot if there was an amount of energy bought from the market that could not be used by the participant due to insufficient demand. That is, $\delta_{p,t} = max(B_{p,t} - C_{p,t}, 0)$.

Definition 2: A participant can have *Uncapitalized Generation* $\gamma_{p,t}$ on a timeslot if there was an amount of energy it could have produced that was not sold on the market, and could not be used to service its internal demand. This could happen due to trading inefficiencies, that is, it was unable to sell all of its excess production. Additionally, due to forecast errors, the participant might have sold less than it should have, or bought energy when it could have used its own generation. That is, $\gamma_{p,t} = max(P_{p,t} - S_{p,t} - max(C_{p,t} - B_{p,t}, 0), 0)$.

Definition 3: An *Unnecessary buy* $\beta_{p,t}$ occurs when a prosumer, a participant with generation capacity, buys energy from the market in lieu of using its internal production. That is, $\beta_{p,t} = max(B_{p,t} - max(C_{p,t} - P_{p,t}, 0), 0)$, if $P_{p,t} > 0$. Unnecessary buys are caused exclusively by forecast errors.

Definition 4: An *Unnecessary sell* $\sigma_{p,t}$ occurs when a prosumer sells energy to the market that could have been used to abate its internal demand. That is, $\sigma_{p,t} = max(S_{p,t} - max(P_{p,t} - C_{p,t}, 0), 0)$, if $P_{p,t} > 0$. Unnecessary sells are caused exclusively by forecast errors.

The demand imbalance measures the amount of energy for which a participant would have to pay penalties. If it buys more energy from the market than it can use, this results in a broken contract. A "supply imbalance" can also be considered when a participant sells more than it can produce. However, because generation forecasting errors are not considered, the supply imbalance will always be zero in our case.

Uncapitalized generation measures the amount of energy a participant could not capitalize on. This happens either due to an inability to sell it on the market or through miscalculation given the demand forecasting errors, which resulted in it not selling as much as it could have. We make no assumptions as to what happens to this energy, if the participant ramps down its production to avoid possible imbalances, or if the energy is injected into the grid anyway. As such, it may or may not be penalized. In any case, it characterizes the opportunity cost of the prosumer given that it did not sell, or use the energy itself.

The unnecessary buys and sells measure the volume of erroneous trades on the market by the participant. The level of their impact is directly related to the transaction costs of the trades. For instance, in the case of an unnecessary sell, in certain circumstances it could make economical sense to sell the entire capacity on the market, rather than use it internally. This would only happen if the acquired revenue is greater than the costs and savings of using the energy. A similar point can be made about unnecessary buys.

V. The Impact of Individual Trading

In this part of the evaluation, we measure the impact of forecasting errors on the NOBEL market when all participants are trading individually. We compare the outcomes of the simulation under two cases that we term *Ideal* and *Predicted*. In the ideal case, the participants trade based on their real demand profile, that is, there are no prediction errors. In the predicted case, they trade based on their predicted demand profile, resulted from the SN algorithm. The number of participants having a PV capacity varies from 10% to 100% of the total number of participants, in steps of 10%. Thus, we can evaluate the effects of forecasting errors on the market, under different levels of the PV penetration. For each penetration level and case a single trial was conducted. The same random number generator seed was used in all experiments, therefore guaranteeing that the same participants have PV installations between each case.

In the ideal case, given that there are no forecasting errors, the demand imbalance, unnecessary buys and unnecessary sells measurements are always zero. However, the participants can have some uncapitalized generation due to trading-strategy inefficiencies that result in it not being able to sell everything that was offered into the market. Additionally, depending on the level of PV penetration, there can be intervals where more supply is available than demand on the market; this is called the excess generation. Figure 3 shows the sold, unsold, and excess generation as a percentage of the total generation. It also depicts the total generation output (MWh) in the system over the entire simulated period for each level of PV penetration.

The introduction of prediction errors causes the amount of uncapitalized generation to increase dramatically as depicted in Figure 4. In the ideal case, between 0.56% and 2.24% of the usable generation goes uncapitalized due to inefficiencies in the trading behavior. However, in the predicted case, with the same trading inefficiencies the incurred uncapitalized generation was between 9.33% and 11.26% of the total usable

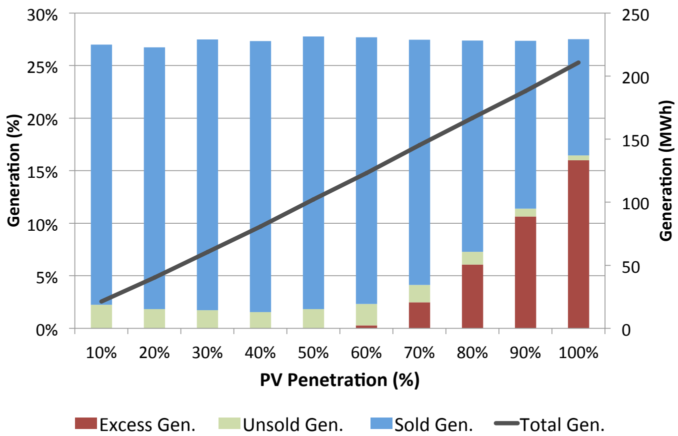

Figure 3. The outcomes of the traded generation as a percentage of total generation, and the increase in total generation (MWh) as a result of increased PV penetration.

generation. This already illustrates how important accurate forecasts will be for market participation.

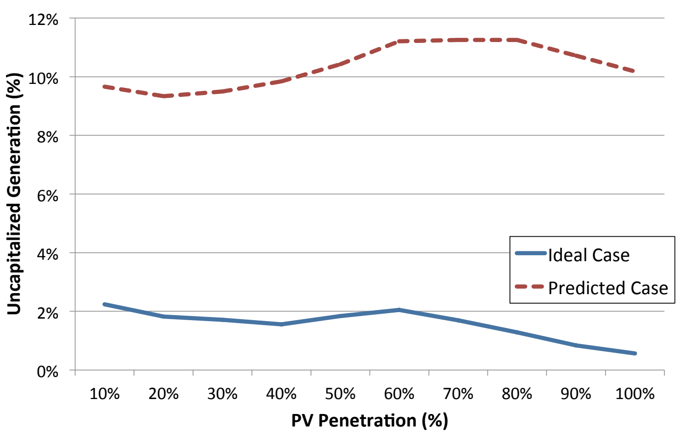

Figure 4. The total uncapitalized generation as a percentage of the total usable generation (total generation – excess).

Forecast errors are responsible for erroneous trading and demand imbalances. They can cause participants to buy more or less than they require, or sell energy that they could use. Furthermore, the error could be so severe that a prosumer could miscalculate its role entirely, acting as buyer when it should have been a seller, and vice-versa. The total demand imbalance, unnecessary buys and unnecessary sells measured in each scenario are depicted in (Figure 5). We observe that while the share of unnecessary buys grows exponentially, the shares of unnecessary sells and demand imbalance grow only slightly. To understand this, one must be reminded that unnecessary buys and sells measure only prosumer behavior, and that the number of prosumers relative to consumers on the market grows as the PV penetration increases. Hence, while most of the electricity available for sale on the market is sold, leading to the very slight growth in unnecessary sells, the portion on electricity that goes to prosumers increases more dramatically as the number of prosumers increase. The demand imbalance grows slightly for similar reasons. Prosumers, due to their internal production, will have on average smaller demand imbalances than consumers. However, while when there is little electricity available on the market most of it goes to consumers, when there is a lot it goes to the prosumers. Thus, stabilizing the share of demand imbalance.

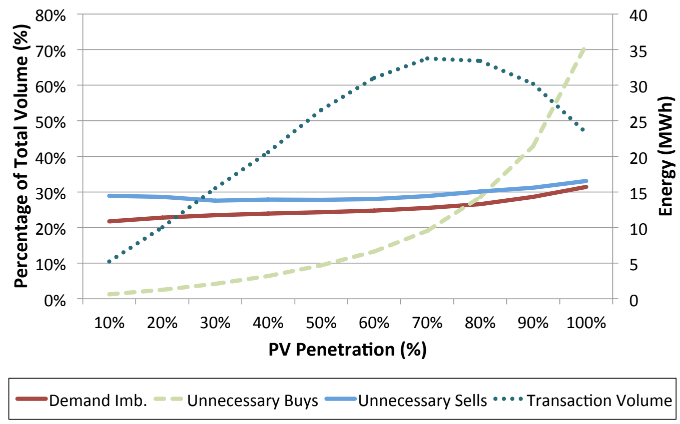

Figure 5. Erroneous transaction volume as a percentage of total transaction volume

As we have seen from the results, forecasting errors can have a significant impact on the individual market participants. They can result in participants miscalculating their role in the market (mistrading), leading to a significant potential for penalty and opportunity costs. Furthermore, forecasting errors have a serious impact on the overall resource usage efficiency of the system. Inefficiencies in the trading mechanism are responsible for uncapitalized generation, as indicated by the ideal case. As such, while making use of better trading strategies can have a positive impact, finding strategies to reduce forecast errors can be far more significant for the individual traders.

VI. The Benefits of Group Trading

The impact of group trading on the market is evaluated by comparing two cases: the *group case* and the *individual case*. The group case simulates trading on the market with a group. In the individual case, all participants trade individually, as in the individual trading evaluation. A probability of 60% of a participant having a PV installation is assigned in both cases. This penetration level was chosen as it was the highest level that displayed only slight levels of excess generation (around 0.29%). Hence, all of the generation can be used in the system, while any excess generation will only be a small component of the results. The group behaves like any other participant in the market; the only difference is that it trades based on its aggregated generation capacity, and on the prediction of the aggregated demand.

Within this evaluation framework, we conduct two experiments. In the first, we evaluate the performance of a small group of consumers, demonstrating the positive effects of their increased forecasting accuracy. In the second experiment, we simulate the participation of mixed a group of consumers and prosumers, and evaluate not only their performance, but also their impact on the market as whole.

A. Consumer Group

The group considered is constituted of 50 randomly chosen consumers (i.e. participants without generation capacity). The average individual MAPE of the demand forecasts of these individuals is 44.62%, while the group's MAPE is 10.09%. Since they are consumers, only the measurement of demand imbalance is pertinent. The performance of the group, and of its participants in the individual case, is depicted in Figure 6.

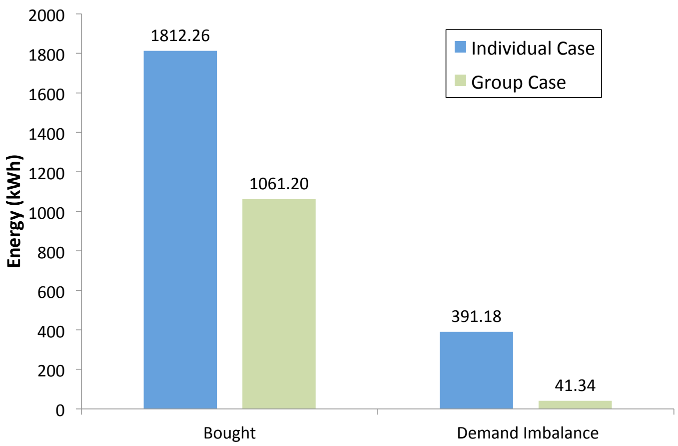

Figure 6. The performance of a consumer group compared to the individual performance of its members.

From Figure 6, the total volume of purchased electricity in the group case decreased by approximately 41% due to trading strategy inefficiencies. However, the demand imbalances decreased by almost 90%. Relatively speaking, around 21.58% of the electricity bought in the individual case leads to potential penalty costs, which is in contrast with the 3.90% of the group case. These results clearly highlight the positive impact of the increased forecasting accuracy.

B. Mixed Group

In this experiment, a location-based selection is adopted, that is, the group is composed of geographically proximate participants, which can be seen as a small neighborhood [23]. This group contains 183 participants with an average daily consumption of $1.3MWh$. The distribution of the MAPEs of the demand forecasts for each of the participants in the group is depicted in Figure 7. Within the 183 group participants, 108 are prosumers.

Although the average individual MAPE for participants of the group is 48.53%, as a group they achieve MAPE of 10.59%. That is, the predictability of the group is nearly five times better than the individual average. For the investigated month of September, the total energy consumed by the group is approximately $38MWh$. If loads are predicted individually, the absolute prediction error results in $20MWh$ (52%), while as a group it results in only $4MWh$ (10.6%).

The evaluation measurements are aggregated over all participants in both cases and compared. The percentage decrease in the evaluation measurements between the individual and group cases is depicted in Figure 8. As seen, the introduction of a group in the market causes a reduction in the aggregate of

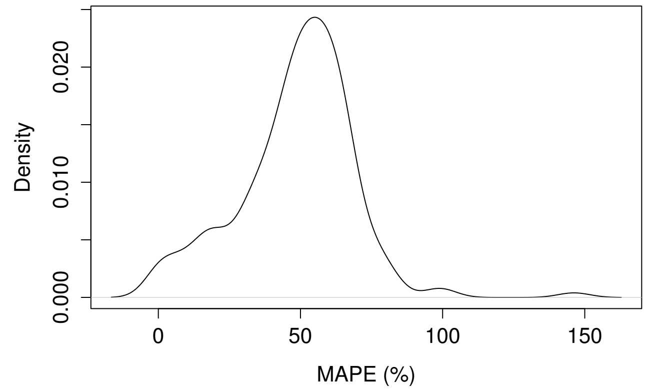

Figure 7. The distribution of the MAPEs of the individuals of the selected group.

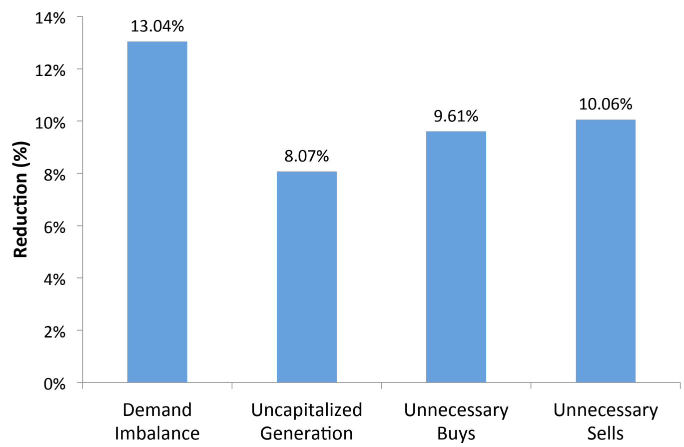

Figure 8. The percentage reduction in the aggregate evaluation measurements between the individual and group cases.

all evaluated measurements. The same behavior can be seen when comparing the group performance and the aggregated performance of the group members in the individual case (Figure 9).

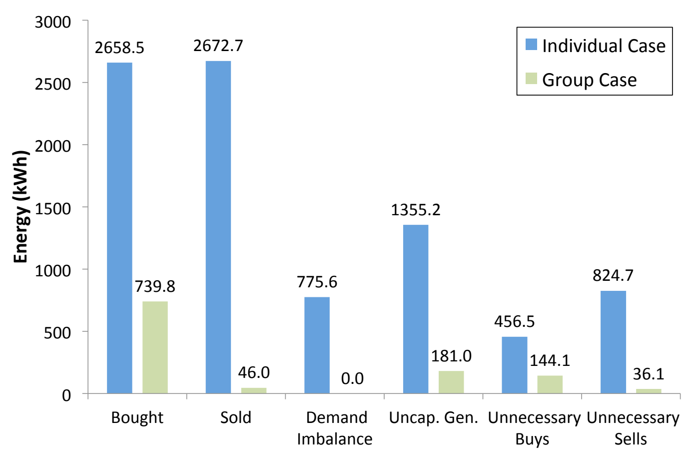

Figure 9. A comparison of group performance vs. the aggregated performance of the individuals. The amount of energy bought and sold is also added for reference.

We observe that the group performs far better than the aggregate of the individuals in the individual case. However, in a group scenario, a prosumer's surplus generation, which normally would have been placed on the market, is now shared between the members. Therefore, the decrease in uncapitalized generation (86%) and unnecessary sells (95%) is largely due to the drastic reduction in the amount of generation placed on the market. However, the increased forecasting accuracy has contributed significantly to the group reduction in unnecessary buys (68%) and in demand imbalance (100%), the latter being the major penalty component as it represents a broken contract. The performance improvement of the group also implies multi-party benefits. For instance, its future behavior is better assessed, any penalties from erroneous behavior are reduced in total, and depending on the cost mitigation policies of that group, this could imply smaller market-participation costs for all participants. Thus, the latter could enable more effective market participation.

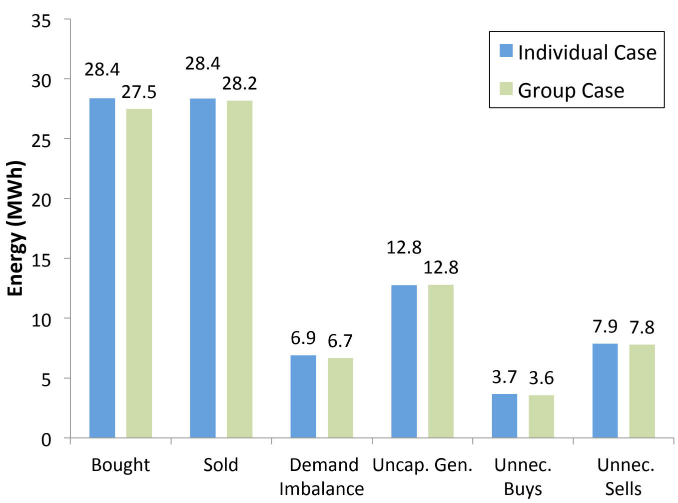

Figure 10. The aggregate measures for the participants that were not part of the group in the individual and group cases. The amount of energy bought and sold is also added for reference.

In contrast, the aggregate performance of the non-group members as depicted in Figure 10, reveals that only marginal, if any, improvements are observed. This means that even if the market was performing a bit better overall, closer to optimum with fewer erroneous transactions, the non-grouped participants would not benefit as much as the grouped ones. Hence, we may derive that any efforts to enhance the behavior of the market participants, for instance by grouping, would have an impact on the market and the rest of the participants. However, the latter would likely be minimal.

Even though the group performs better than the aggregate of its members, there are cases where an individual can perform better, in one measurement or another, by acting individually. For instance, if the group measurements are apportioned to each member in proportion to their demand and supply, one participant displayed an increase in all measurements, five additional participants showed an increase in unnecessary sells, and several participants showed an increase in unnecessary buys. In Figure 11, we depict the sorted differences in these measurements, for each participant, between the group and individual cases. Around 50% of the participants either had

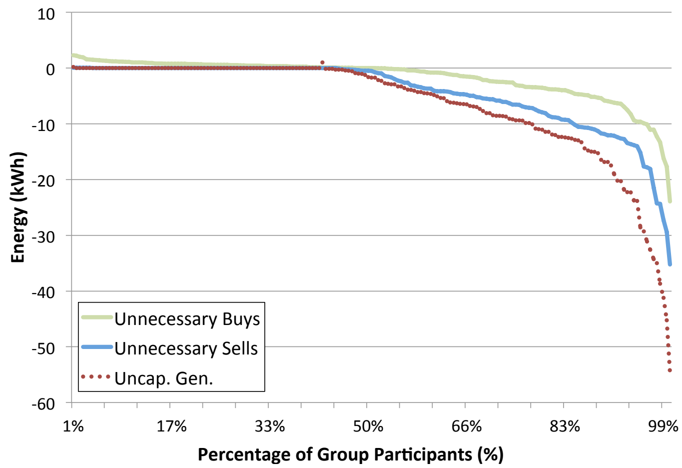

Figure 11. The difference in unnecessary buys/sells and uncapitalized generation, for the group participants, between the group and individual cases. The differences in each measurement are sorted from highest to lowest. A negative value represents an improvement.

no change or an improvement in unnecessary buys, and of the remaining participants, around 70% had an increase of less than $1kWh$ for the simulated period, and the largest increase was around $2.3kWh$. However this comes at the benefit of sharing in the cheaper supply offered by the prosumer members. Of the prosumer's of the group (60%), only 0.5% had an increase in unnecessary sells, which in all cases were negligible (around $50Wh$). Furthermore, only a single prosumer showed an increase in uncapitalized generation, of $180Wh$. Figure 11 also shows that the positive effects of grouping are far larger than the negatives.

C. Group Trading Remarks

As can be seen, groups offer clear benefits for market participation in terms of their potential to reduce penalty costs, such as demand imbalances. Furthermore, when considering mixed-groups, the sharing of generation resources created added-value for both the consumers and prosumers of the group. On the one hand, the participants have access to cheaper, inner-group electricity, which simultaneously increases the utilization of these resources.

In contrast, the overall reduction and cost sharing can lead to a more economically effective form of market participation. These results were achieved through the use of a simple trading behavior and forecasting methodology. This emphasizes that even if more sophisticated methodologies are applied, and still result in uneconomical outcomes for some participants, the barriers for the realization of a local market and effective participation within it can be overcome through grouping.

VII. Conclusion

The transition towards an information-driven smart grid will empower new stakeholders including passive consumers to be active in the electricity supply-chain. This also implies that new energy-management control paradigms, such as financial control systems realized indirectly with the operation of local electricity markets may be a promising route to follow. As seen such approaches may assist towards optimal use of available resources including intermittent renewable generation. In order to harvest the benefits, however, a high degree of forecast accuracy by the participants will be required to ensure that participation makes financial sense.

In this work, we have analyzed real smart metering data, a result that led to an understanding of the impact that grouping has on forecasting errors under different forecasting algorithms. It was shown that forecasting accuracy increases as group size increases, even for small groups, which is our focus. Additionally, we have quantified the effects of forecasting errors on a local electricity market. It was shown, under different levels of PV penetration, the level to which forecasting errors can lead to erroneous trading behavior, creating uncapitalized generation and other opportunity costs and penalties. For instance, at a PV penetration of 50%, over 10% of the total generation capacity was uncapitalized and roughly 10, 25 and 28% of the total traded volume were unnecessary buys, demand imbalances and unnecessary sells, respectively. While needless buying or selling of energy will not necessarily incur costs, as it will depend on the transaction prices (depending on the business model), they represent energy over which the participant has no control.

As a potential solution for this problem, we have investigated the performance of pVPPs, which are virtual groups of participants that act as a single unit on the market. Such a group exploits the positive effects of aggregation on forecasting accuracy and resource sharing. The creation of groups led to a global reduction in potential market related costs. In a consumer group of 50 participants, the percentage of purchased energy that could be attributed to penalties was reduced from 21.58% to 3.90%. In a mixed group of 183 participants (including both consumers and prosumers) we found an overall reduction in uncapitalized generation, erroneous transactions, and imbalances when compared to the aggregate performance of its individuals. Such results are important because future consumers or prosumers may exploit the advantages of coalitions, even small ones, to reduce their electricity-related costs. For example, given the current high costs of solar generation, it would be possible for consumers to share investment costs and accrue other benefits through market participation. Here, we have shown that by acting as a group on local electricity markets, additional benefits can be obtained.

In our evaluation, we have focused on the energy component of the potential penalty and opportunity costs incurred by the participants. As such, future work will concentrate on better defining these costs, and economically evaluating the performance of individuals and groups. In this way, we seek to better understand the forecasting/economical barrier for entering the market and participating effectively as well as assess the multi-stakeholder benefits.

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References

[1] X. Yu, C. Cecati, T. Dillon, and M. Simões, "The new frontier of smart grids," *Industrial Electronics Magazine, IEEE*, vol. 5, no. 3, pp. 49–63, Sep. 2011.

[2] S. Karnouskos, "Demand side management via prosumer interactions in a smart city energy marketplace," in *IEEE International Conference on Innovative Smart Grid Technologies (ISGT 2011), Manchester, UK*, Dec. 5–7 2011.

[3] J. K. Kok, M. J. J. Scheepers, and I. G. Kamphuis, "Intelligence in electricity networks for embedding renewables and distributed generation," in *Intelligent Infrastructures*, ser. Intelligent Systems, Control and Automation: Science and Engineering, R. R. Negenborn, Z. Lukszo, and H. Hellendoorn, Eds. Springer Netherlands, 2010, vol. 42, pp. 179–209.

[4] C. Julian and J. Dobson, "Re-energising Our Communities: Transforming the Energy Market Through Local Energy Production," A ResPublica Green Paper (www.respublica.org.uk), Feb. 2012.

[5] F. Hvelplund, "Renewable energy and the need for local energy markets," *Energy*, vol. 31, no. 13, pp. 2293–2302, 2006.

[6] N. Hatziargyriou, A. Dimeas, A. Tsikalakis, J. Lopes, G. Karniotakis, and J. Oyarzabal, "Management of microgrids in market environment," in *Future Power Systems, 2005 International Conference on*, 2005.

[7] D. Menniti, A. Pinnarelli, and N. Sorrentino, "Operation of decentralized electricity markets in microgrids," in *Electricity Distribution - Part 1, 2009. CIRED 2009. 20th International Conference and Exhibition on*, 2009, pp. 1–4.

[8] D. Ilic, P. Goncalves Da Silva, S. Karnouskos, and M. Griesemer, "An energy market for trading electricity in smart grid neighbourhoods," in *6th IEEE International Conference on Digital Ecosystem Technologies – Complex Environment Engineering (IEEE DEST-CEE), Campione d'Italia, Italy*, Jun. 2012.

[9] European Commission, "SmartGrids SRA 2035 – Strategic Research Agenda: Update of the SmartGrids SRA 2007 for the needs by the year 2035," European Technology Platform SmartGrids, European Commission, Tech. Rep., Mar. 2012. [Online]. Available: http://www.smartgrids.eu/documents/sra2035.pdf

[10] Federation of German Industries (BDI), "Internet of Energy: ICT for energy markets of the future," BDI publication No. 439, Feb. 2010.

[11] V. L. Smith, "An experimental study of competitive market behavior," *Journal of Political Economy*, vol. 70, no. 2, pp. 111–137, Apr. 1962.

[12] P. Vytelingum, S. D. Ramchurn, T. Voice, A. Rogers, and N. R. Jennings, "Trading agents for the smart electricity grid," in *9th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2010), Toronto, Canada*, 10-14 May 2010, pp. 897–904.

[13] R. K. Dash, P. Vytelingum, A. Rogers, E. David, and N. R. Jennings, "Market-based task allocation mechanisms for limited-capacity suppliers," *Trans. Sys. Man Cyber. Part A*, vol. 37, no. 3, pp. 391–405, May 2007.

[14] S. Lamparter, S. Becher, and J.-G. Fischer, "An agent-based market platform for smart grids," in *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: Industry track*, ser. AAMAS '10. Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems, 2010, pp. 1689–1696.

[15] P. Goncalves Da Silva, S. Karnouskos, and D. Ilic, "Evaluation of the scalability of an energy market for smart grid neighbourhoods," in *IEEE 11th International Conference on Industrial Informatics (INDIN), Bochum, Germany*, Jul. 29–31 2013.

[16] D. Ilic, S. Karnouskos, P. Goncalves Da Silva, and M. Jacobi, "Impact assessment of smart meter grouping on the accuracy of forecasting algorithms," in *28th ACM Symposium On Applied Computing (SAC), Coimbra, Portugal*, 18 – 22 Mar. 2013.

[17] J. W. Taylor, L. M. de Menezes, and P. E. McSharry, "A comparison of univariate methods for forecasting electricity demand up to a day ahead," *International Journal of Forecasting*, vol. 22, no. 1, pp. 1–16, Jan. 2006.

[18] R. J. Hyndman and G. Athanasopoulos, "Forecasting: principles and practice," 2012. [Online]. Available: http://otexts.com/fpp/

[19] U. Focken, M. Lange, K. Mönnich, H. Waldl, H. G. Beyer, and A. Luig, "Short-term prediction of the aggregated power output of wind farms – a statistical analysis of the reduction of the prediction error by spatial smoothing effects," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 90, no. 3, pp. 231–246, 2002.

[20] EPIA, "Global market outlook for photovoltaics until 2016," European Photovoltaic Industry Association, Tech. Rep., 2012. [Online]. Available: http://www.iea.org/publications/freepublications/publication/kwes.pdf

[21] E. Matallanas, M. Castillo-Cagigal, E. Caamaño-Martín, D. Masa-Bote, A. Gutiérrez, and F. Monasterio, "Analysis of the self-consumption possibilities in small grid-connected photovoltaic systems in spain," in *Proceedings of the 26th European Photovoltaic Solar Energy Conference*. Munich, Germany: WIP-Renewable Energies, 2011, pp. 4619–4624.

[22] D. Cliff and J. Bruten, "Less than human: Simple adaptive trading agents for CDA markets," in *Computation in Economics, Finance and Engineering: Economic Systems*, S. Holly, Ed. Oxford: Pergamon, 2000, pp. 117–122.

[23] D. Ilic, S. Karnouskos, and P. Goncalves Da Silva, "Improving load forecast in prosumer clusters by varying energy storage size," in *IEEE Grenoble PowerTech 2013, Grenoble, France*, 16 – 20 Jun. 2013.