Evaluation of the Scalability of an Energy Market for Smart Grid Neighborhoods

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***Abstract*—The electric power grid is undergoing fundamental changes in light of the current focus on distributed generation, and in particular renewable generation (e.g., solar and wind). As a result, new methodologies and technologies are needed to effectively coordinate and make optimal use of the these resources. A distribution-system level energy market offers the potential to address this issue by providing an efficient mechanism for the pricing and allocation of resources. Market participants (e.g., households, ESCos, asset managers etc.) can apply economically driven strategies to trade energy while reacting to current and local levels of production and consumption. We evaluate here such a local neighborhood market and investigate its scalability under different numbers of participants and different penetrations photo-voltaic (PV) generation. The evaluation is carried out by simulating market operations under realistic production and consumption conditions. Results showed that the proposed market model scales well against both parameters.**

I. INTRODUCTION

The increasing penetration of Distributed Energy Resources (DERs) is disrupting the standard broadcast-style power-grid model. It is transitioning the grid towards a decentralized system where a large numbers of small-capacity generators (DERs) are located on premises, connected to the distribution system. Examples include storage devices, electric vehicles, photovoltaic (PV) installations, wind generators, and μCHP units. As their uptake increases, new management strategies will be required to coordinate these resources. Additionally, the intermittent nature of some renewable DERs means that some level of demand response will be needed to make maximal usage of these resources.

Integrating and making efficient use of DERs under highly dynamic conditions is a key challenge for the Smart Grid and has been gaining wide interest in the research community [1], [2]. The emerging Smart Grid [3] empowered by modern IT technologies is promising a more versatile and intelligent network of collaborating actors that will eventually lead to better utilization of its resources, better management, and of course will enable us to achieve goals such as energy efficiency. Currently there are several projects underway in Europe investigating the multiple facets of the Smart Grid [4].

Energy markets can enable interactions between the multiple envisioned Smart-Grid stakeholders [5], [6] in an economically-driven way. These markets may be at local levels, such as, neighborhood or city-wide, and act as a method to indirectly manage Smart-Grid resources based on its outcomes (e.g. energy price as a result of trading). Furthermore, efforts towards Demand Side Management (DSM) and Demand-Response (DR) can be highly assisted by the existence of such a market [6].

In this context, participants could leverage market information to plan and take optimal advantage of local conditions of production and consumption. As such, the market can be used as a self-regulating mechanism for dictating which generation units get dispatched, at what level, and at what time. All based on financial assessments of potential profits. A market could also enable "prosumers" (consumers with installed generation capacity) to further capitalize on their investment by selling off unneeded capacity. For the consumers, the market would offer another avenue for energy procurement and a way to reduce energy-related costs.

The NOBEL market [7] adheres to such a market model, and enables participants to trade energy based on their forecast levels of production and consumption. However, as will be discussed, the evaluation of the NOBEL market, and indeed others, has mainly focused on the efficiency of the proposed models. In this work, we investigate the scalability of the NOBEL market against growing numbers of participants, and various penetration rates of DERs. In this case, PV generation is considered. The evaluation is carried out using real demand profiles and simulated PV output based on weather data. The issue of scalability is an important one, as it allows us to identify the necessary conditions for a successful deployment of the "neighborhood energy" market.

II. CONTINUOUS DOUBLE AUCTION MARKETS

New electricity market models are the heart of major roadmaps for the Smart Grid [5]. Our research focuses on Continuous Double Auction (CDA) based models. Their decentralized nature makes them highly scalable and robust. In CDAs, the market clears continuously as new orders arrive; this is in contrast with discrete clearing mechanisms, where all the orders are aggregated and an optimal allocation is made by a central entity, or auctioneer. In a CDA, the allocations emerge from the interactions between the participants and can change as new information is made available to the traders. In our view, this feature makes CDA-based models better candidates for a local energy market since it allows participants to easily adapt to changing conditions that could in turn lead to a better usage of the resources.

Some CDA-based energy market models can already be found in literature. For instance, [8] proposes a day-ahead

CDA based market, extended with a real-time energy balancing capability. It also includes a security component that takes into account the current system state and appropriately prices the flow of electricity through transmission lines to guarantee system stability. The model is tested against different grid topologies, transmission line capacities, and trading agent strategies that are compared against the optimal behavior. The results showed that 99% efficiency could be obtained, with a lower bound of 86%. Although this model applies to a transmission system, it provides some evidence that CDA models can be highly efficient.

In other work [9], a CDA model is proposed for resource allocation problems where suppliers have limited capacity, and consumers have inelastic demand. As such, transactions only occur when the entire quantity of a buy order (or set of buy orders) can be matched by one or more sell orders. These criteria are related to the constraint of inelastic demand. In this case, the buyer needs its entire demand satisfied in order to perform its tasks. The price of a transaction is set so that profits are equally divided between buyers and sellers. The results show that, even under simplistic trading behaviors, the sellers' prices can closely resemble the prices found in a centralized optimal allocation mechanism.

The constraint of inelastic demand might be too strong for a distribution-system market. In some cases, there may not be enough resources to meet the demand. Therefore, we take a pragmatic approach and view the market as a tool for diversifying the supply of the consumers. A portion of demand can be acquired through the market, while the remainder through the retailer. Additionally, calculating generation costs can be straightforward (i.e., fuel costs and capacity factors can be easily estimated), but for buyers, it may not be as simple. A household might not be too concerned about the micro-cost associations of their household tasks. However, in this case, the retailer costs can be used as a basis for trading on the market. Any price smaller than the retailer contract price will represent a saving. Of course, this entails that the electricity costs on the market are smaller than that of the retailer costs. This is not currently the case, but, for instance, as DER prices decrease and retailer prices increase, or other incentives addressing sustainability may exist, we assume this might still be a valid business case in the future.

The NOBEL market [7] is more flexible in its orders and clearing mechanism. The market is composed of a series of concurrent CDAs, called timeslots. Every timeslot represents an interval (15 minutes) in the future where participants can place their orders. The sequence of timeslots offers a platform for continuous energy trading, where every passed timeslot (on the tail of the sequence) is replaced by a new one in future (on the head of the sequence). The placement of an order in a timeslot triggers the clearing mechanism. Transactions occur when orders match in price (i.e., the buy order price is greater or equal to the sell order price). Unmatched, or partially matched, orders are stored in the timeslot's order book that is publicly accessible by the market participants. The model also 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. However, the usage of these attributes is optional to the traders. So far, the NOBEL market has been evaluated in terms of the usage of its underlying available resources. Under simple trading behaviors (i.e. trading at random prices), a lower-bound of about 75% efficiency was determined [7].

The number of participants in such a market may vary due to size of the distribution system, or even the level of adoption. Additionally, different distribution systems might accommodate different levels penetrations DERs. With this in mind, we extend the NOBEL market evaluation by considering the issue of scalability and how the market operated under different scenarios defined by the aforementioned parameters. To do so, market operations are simulated under realistic consumption and production conditions.

III. Experiment Realization

A discrete agent-based simulation environment has been developed to simulate the functioning of the market and the traders. In any simulation, there is one market agent, which is in charge of opening and closing the trading timeslots, and a configurable number of trading agents. The trading agents simulate the participants in the market. At the end of each step, once the trading agents have run, the market agent closes the most recent timeslot, and opens a new timeslot in a rolling-window fashion. Each trading agent runs its trading algorithm 1000 times per time step in a random order. The attributes of each agent (e.g., consumption, production, energy bought/sold, etc.) for each timeslot are recorded, in addition to all orders and transactions in the market.

The trading agents, for now on referred to simply as "agents", are defined by three components: (i) their consumption profile, (ii) their production profile, and (iii) their strategy. The consumption profile used for the agents is based on real measurements taken from the participants in the NOBEL project trial. The measurements are interpolated over 15 minute intervals and converted to Wh, as this is the unit of trade in the market. A database with demand profile of 1897 real NOBEL trial participants, between $05-Sept-2012$ and $13-Sept-2012$, is used, with each profiles being assigned randomly to each trading agent. The data set is mixed containing consumption profiles for households and in-city commercial establishments. The cumulative distribution of the average daily consumption (kWh) of each participant is depicted in Figure 1.

In our experiments, there are two types of agents, consumers and "prosumers". The production profile for the "prosumers" is created by simulating the a PV installation. The PV production (Wh) of a given installation i, for a particular 15 minute interval t, is given by $E(t) = \eta\alpha I_g(t)\omega(t)\tau$. 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), $0 \leq \omega(t) \geq 1$ is a dimensionless scaling factor in function of the weather conditions (e.g., clear sky is 1

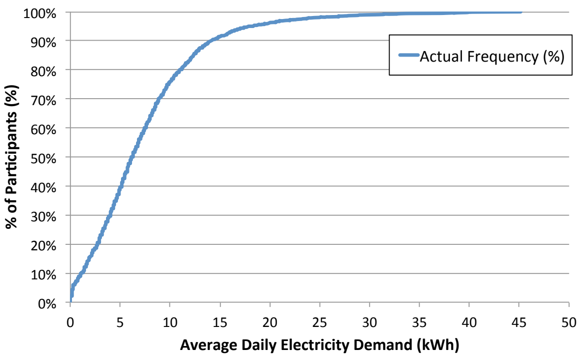

Figure 1. The cumulative distribution of the average daily consumption of the participants

while a thunder storm is 0), and τ is the timeslot duration in hours (0.25 in this case). The area of the installation assigned to an agent is calculated so that it can produce 50% of the participant's total demand within the simulated period. For instance, if an agent would consume $10kWh$ within the entire period, its PV installation would produce up to $5kWh$ for same period.

Finally, the simulated production is calculated using the daily irradiation and weather data for the city of Alginet (Spain), where the NOBEL trials took place in 2012. The daily irradiation utility offered by JRC's Photovoltaic Geographical Information System [1], and the used weather factor is offered by Wunderground [2]. An example of one agent's consumption and production profiles for a day is depicted in Figure 2.

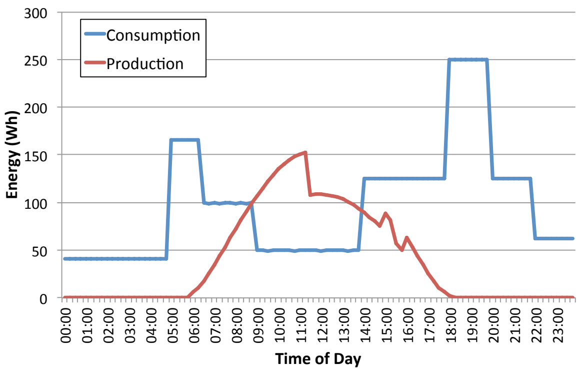

Figure 2. An agent's consumption and production profile for one day

To simulate the trading behavior of the agents, the Zero-Intelligence-Plus (ZIP) strategy [10] is employed. In ZIP strategy, an agent tries to buy or sell energy through the market, while attempting to maximize its profit. The agent uses simple heuristics to adapt its profit margin, based on its limit price to buy or sell, in response market events. The agent keeps track of the last order q, whether it was a *buy* or a *sell*, and if it resulted in a transaction. Based on this information, the agent makes a decision to either increase or decrease its profit margin, which is then used to calculate their new price.

When an agent is buying, its limit price will be defined by its retailer contract price for the particular timeslot. It is assumed that the agent would be willing to pay its contract price at limit in order to buy from the market. The flat-rate retailer contract of the NOBEL trial was assigned to the participants, thus $14c/kWh$ was assigned to each agent. The limit price for sellers is defined by their production costs. Since PV costs are still relatively high, an assumed production cost of $5c/kWh$ was used. The effects of different costs and generating technologies is out of the scope of this work and is left for future research.

For each timeslot on the market, each "prosumer" must decide if it will be a buyer of seller. Consumers will always be buyers. Every "prosumer" examines the difference between its consumption and production for the particular timeslot to make this decision. If the consumption is greater then its local production, the agent will attempt to buy the difference from the market. Alternatively, if the production is greater, the agent will attempt to sell the difference on the market. At each iteration, the agent will first calculate its profit margin based on the ZIP behavior. Once the profit margin is determined, the agent's price is calculated. It will then remove its current order from the market, if one exists, and place a new order with the remaining trading quantity with the newly calculated price. As an agent trades electricity in the market, its remaining quantity (to buy or sell) is updated. Once an agent has no more energy to buy or sell, it no longer participates in the market. The agent parameters are set as described in [10] and no parameter tuning was performed. In this way, a baseline for future comparison can be established. For simplicity, the agents only trade on the nearest open timeslot and forecasting errors are not considered.

IV. Evaluation

The scalability of the market is evaluated through simulated scenarios defined by two key parameters. The first parameter is the number of agents, $\alpha \in \{100, 500, 1000, 1500, 1897\}$. By varying the number of agents, we can investigate the suitability of the market for different distribution-system sizes, as well as different levels of participation. The second parameter is the probability of an agent having a PV installation, $Pr(PV) \in \{10\%, 20\%, 30\%, \ldots, 100\%\}$. Different levels of DER penetration, in this case PV installations, will have direct impact on market prices. The higher the available supply, the lower the price will be. This is an important parameter, as price dynamics of the market will impact the investment decisions of the participants. If prices are relatively high, it may be worth acquiring or installing additional capacity. However, if they are low, it may be worth installing storage capacity to "spread" its production to market timeslots of low availability [11].

For each parameter pair, a simulation scenario is run several times to obtain a distribution of the measured outputs. Due to time constraints, different numbers of experiments are run for each scenario as the time taken to execute an experiment

[1] http://re.jrc.ec.europa.eu/pvgis/apps4/pvest.php
[2] www.wunderground.com

increases with number of agents. The scenarios with α of 100, 500, 1000, 1500 and 1897 agents are run 300, 100, 50, 50 and 50 times, respectively. The number of repetitions was chosen experimentally by observing the convergence of the variance of the output measurements.

A. Supply/Demand Characteristics

In order to accurately interpret the results, the relationship between the supply and demand for each experiment, is measured. This relationship is important as it directly impacts the prices on the market. As such, two measurements are taken: the relationship of the total production and consumption in the experiment, ρ, and the average relationship between supply and demand offered on the market per timeslot, ρ_m. These are formally defined as follows:

- $\rho = \frac{\sum_i^n \sum_j^m P_{i,j}}{\sum_i^n \sum_j^m C_{i,j}}$, where n is number of agents, m is the number of timeslots, and $P_{i,j}$ and $C_{i,j}$ are the production and consumption (Wh) for agent i in timeslot j. This measurement represents the macro, or overall, relationship between supply and demand.
- $\rho_m = \frac{\sum_j^m \frac{s_j}{d_j}}{m}$, where m is the number of timeslots, and s_j and d_j are the aggregate supply and demand (Wh) offered into the market for timeslot j. In this case, only timeslots where there can be trading ($s_j > 0$) are considered. This measurement represents the micro, or timeslot-based, relationship between supply and demand.

The results show that the average ρ stays relatively constant within each PV probability level (as depicted in Figure 3). However, the scenarios with 100 agents show a higher average ρ_m when compared to the scenarios with a higher number of agents (as depicted in Figure 4).

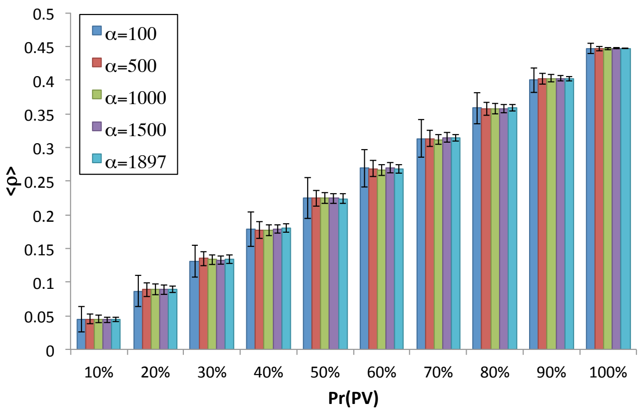

Figure 3. The average ρ of the simulated scenarios. Error bars represent one standard deviation.

This shows that while the scenarios (with the same $Pr(PV)$) may be on average similar on the macro level, at the micro (timeslot) level they tend to behave differently for low numbers of agents. This difference plays an important role, as it may result in different market behavior.

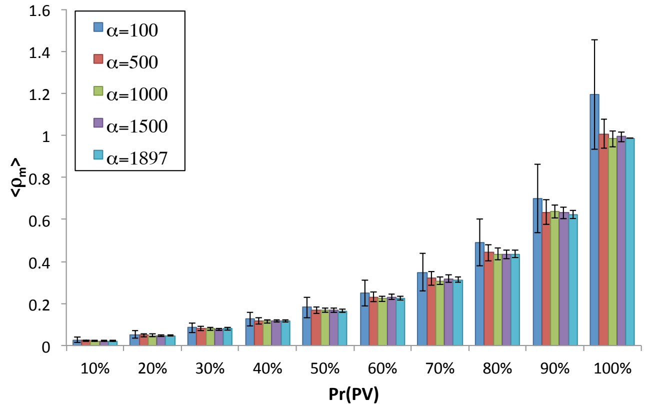

Figure 4. The average ρ_m for each of the simulated scenarios. Error bars represent one standard deviation.

B. Price Behavior

The price behavior on the market is an important aspect as it is what influences the participation on the market. To evaluate this behaviour, two measurements are taken for each scenario:

- the average transactions price over all transactions in the experiment, $p_a v$. That is, the expected energy price for the scenario.
- the standard deviation of transactions prices over all transactions in the experiment, $\sigma(p)$. This measurement shows the amount of variability in the transaction prices.

As can be seen in Figure 5, the average transaction prices are reduced with the increase in $Pr(PV)$. This is seen when comparing any scenarios with the same number of agents. However, the scenarios with 100 agents experienced a lower average $p_a v$ compared to the others, although the effect decreases at high PV penetrations. This phenomenon might be explained by the higher ρ_m observed in these scenarios (Figure 4) for lower values of $Pr(PV)$, that is, the higher amount of offered supply depressed prices slightly. For higher penetrations $Pr(PV) \geq 90\%$, the effect is almost non-existent. This could be explained by inefficiencies in the trading strategy. While there was, on average, more supply available on the market, the trading strategy was unable to take maximal advantage of it, pushing up prices. This aspect is investigated in the following section. In any case, the price differences found are small. The biggest difference found was roughly 0.2 c/kWh, and the magnitude of the effect diminishes with the increase in $Pr(PV)$. Therefore, we can conclude that, in practical terms, the market scales well against the tested parameters.

The variation in the transaction prices, $\sigma(p)$, for each scenario is depicted in Figure 6. As can be seen, average $\sigma(p)$ increases with the increase in $Pr(PV)$. Because of the hyperbolic nature of PV production, as more PV installations get added to the system, there is also an increase in the variation of ρ_m. This leads to higher variations in the transactions prices. That is, for low penetrations of PV, it could be expected that there will be relatively low levels of supply offered on the

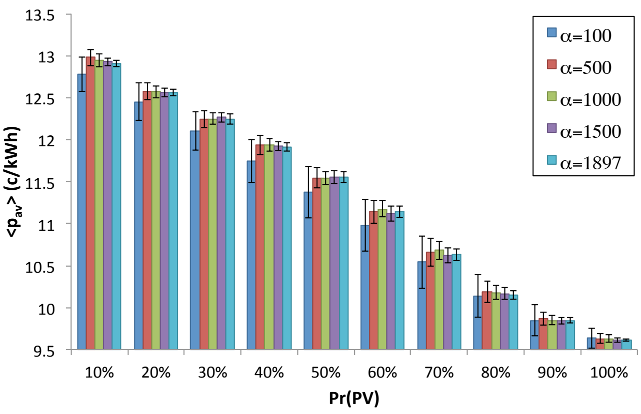

Figure 5. The average $p_a v$ for each simulated scenario. Error bars represent one standard deviation.

market throughout the day. However, for high penetrations, there might be low levels of production close to sunrise and sunset, but high levels around midday.

Within each PV penetration level, a lower number of participants tend to show a higher average variation in transaction prices. However, the effect diminishes with the increase in PV penetration. Therefore, while there is no practical difference in the average prices, the number of agents, for some scenarios, can have a significant impact on price variation.

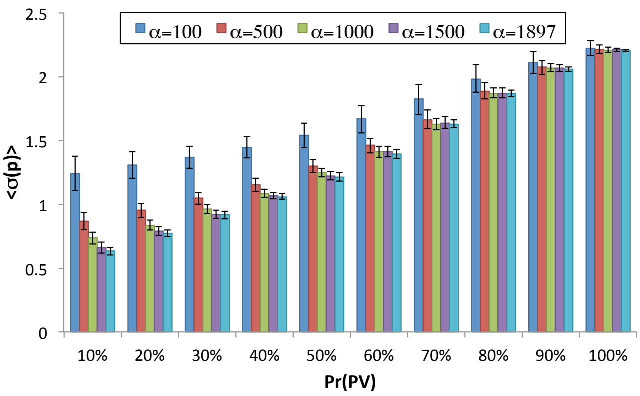

Figure 6. The average standard deviation of the transaction prices ($\sigma(p)$) for each simulated scenario. Error bars represent one standard deviation.

C. Resource Usage Efficiency

The resource usage efficiency measures the level of PV utilization in the scenarios. To assess the resource usage efficiency of the scenarios, two measurements where taken:

- The resource usage efficiency, $\phi = \frac{\sum_{j}^{m}(P_j - s_j) + T_j}{\sum_{j}^{m} S_j}$. Where P_j is the total production, s_j is the total offered production, and T_j is the total transacted volume on timeslot j, respectively. Essentially, ϕ is the ratio of the total production used (both internally and sold on the market) to total production.
- Excess production, $\epsilon = \sum_{j}^{m}(max(P_j - C_j, 0)$. Where P_j is the total production and C_j is the total consumption on timeslot j, respectively. This measurement measures the amount of production that could not have been sold as there was not enough demand on the market.

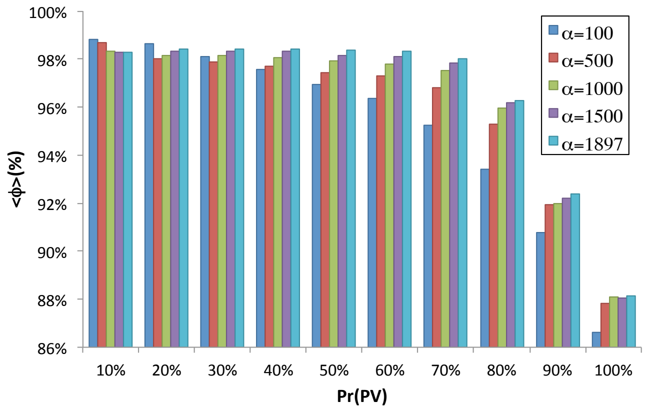

Figure 7. The average ϕ for each simulated scenario

As can be seen in Figure 7, on average ϕ remains relatively similar between market sizes (α) for $Pr(PV) < 50\%$. For $Pr(PV) \geq 50\%$, two effects can be observed: on average ϕ (i) improves with increasing numbers of agents, and (ii) decreases with the increase in $Pr(PV)$. The first effect can be explained by inefficiencies in the trading strategy. Essentially, less of the available production is traded for smaller market sizes. The second effect is explained by the increasing level of excess production in the system (Figure 8).

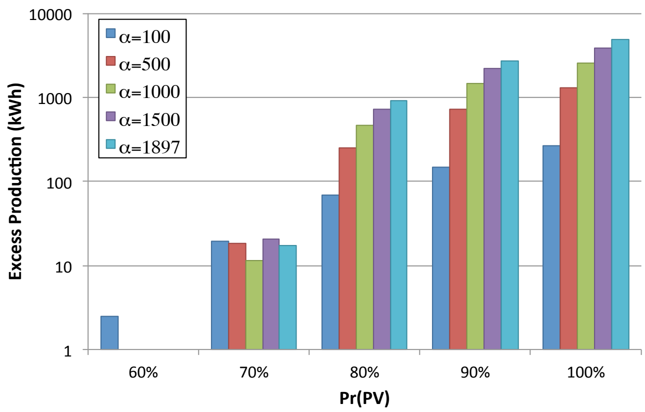

Figure 8. The average aggregate excess production (kWh) for each simulated scenario. The data is depicted on a logarithmic scale.

The same trading strategy is used in all scenarios. The results suggest that trading strategies may need to be tailored to the specific conditions on the market. Furthermore, the results show a high ϕ for most $Pr(PV)$ levels. This means that, at least within the framework of the evaluation, there is limited scope for demand response (DR). Since, in most cases, not even the usual demand can be met during times of high resource availability (as indicated by the average resource usage efficiency), there will be little impetus for consumers to adjust their consumption. Therefore, for the market to foster DR behavior in its participants, there must be some level of excess production in the scenario. However, a flat retailer tariff scheme, as well as no storage, is assumed. It would be interesting to evaluate in the future how the market could complement exogenous demand response schemes, such as, time-of-use tariffs and storage, to improve the overall system.

V. Discussion and Conclusions

We have evaluated the scalability of the NOBEL electricity market against a varying number of participants and different penetration rates of PV generation. The evaluation focused on the changes in the relationship between production and consumption among the scenarios, as well as the resulting expected energy prices. The results showed that while there were small differences in the average aggregate (macro) relationship between supply and demand, more pronounced differences are found in the average (micro) timeslot behavior for this relationship. This micro behavior leads to marginal differences in the expected energy prices, for each level of PV, between the markets with difference numbers of participants (around 0.2 c/kWh in the most extreme case). It also led to increased variation in transaction prices for lower number of market participants. This shows that the number of participants has only a slight effect on market prices. This is an important result, as we envision that participants may form groups and act in unison on the market. In this way, they can share the risks and rewards of market participation as well as incur other benefits such as improved forecasting accuracy [12]. The results show that the market can be resilient to micro (timeslot) changes in supply and demand against a constant macro (aggregate) supply/demand relationship.

Additionally, the resource usage efficiency of the scenarios were measured. Results showed that the efficiency tended to deteriorate for low number of participants at high PV penetrations. These results, along with the increase in transaction price variation, suggest that the trading strategies employed by the participants need to be adjusted to the underlying market conditions.

There are two major goals behind distribution-system scale energy markets: (i) to coordinate the production of DERs and (ii) to provide platform for demand response (DR) to reduce peak consumption. The results provide further evidence that markets, especially ones based on CDA models, can meet the first goal. Within the framework of the evaluation, it would likely take a high penetration of DERs to provide participants with enough impetus to engage in DR. For low penetrations, consumers will have no extra benefit in shifting their demand, as they cannot even cover their usual demand with the available market supply. Additionally, producers have little incentive to invest in storage capacity, which could be used to target periods of high demand. That is, there is enough demand on the market for producers to sell their entire capacity at good prices. Therefore, the second goal could only be reasonably met under high PV penetrations or exogenous incentives such as time-of-use tariffs.

In future work, we target evaluating the market under different generation technologies, and generation mix, as well as storage. Furthermore, we plan to focus on the effects of forecasting errors by the participants (not considered in this evaluation), as well as the effects of groups of participants on the market. We also aim to further investigate market conditions necessary to foster a high level of DR.

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