Exploring retail energy markets through competitive simulation

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Abstract

Future sustainable energy systems will need efficient, clean, low-cost, renewable energy sources, as well as market structures that motivate sustainable behaviors on the part of households and businesses. "Smart grid" components can help consumers manage their consumption only if pricing policies are in place that motivate consumers to install and use these new tools in ways that maximize utilization of renewable energy sources while minimizing dependence on non-renewable energy. Serious market breakdowns, such as the California energy crisis in 2000, have made policy makers wary of setting up new retail energy markets. We present the design of an open, competitive simulation approach that will produce robust research results on the structure and operation of retail power markets as well as on automating market interaction by means of competitively tested and benchmarked agents. These results will yield policy guidance that can significantly reduce the risk of instituting competitive energy markets at the retail level, thereby applying economic motivation to the problem of adjusting our energy production and consumption patterns to the requirements of a sustainable future.

Introduction

The energy sector will experience fundamental change over the next ten years. The cost of fossil fuel is continuously increasing, there is an urgent need to reduce CO_2 emissions, and the United States and European Union are strongly motivated to become independent from imported energy. One result will be increasing numbers of distributed, intermittent renewable energy systems, which will be connected to the distribution grid at the bottom (retail) level rather than at the top (wholesale) level. This trend conflicts with the current top-down grid control infrastructure, where a few control centers manage large power plants and top-level switchgear such that energy output meets energy demand in real time. It also conflicts with the way electrical power is sold at the retail level; consumers currently lack both information and economic motivation to adjust their demand to the availability of clean sources of power.

At its core, this is a problem of distributing resources among self-interested parties, a problem that markets can solve. In a regional retail energy market, participating brokers would be responsible to assemble portfolios of contracts with energy suppliers and users. Their portfolios must then be managed to maintain a near-optimal balance between production and consumption of electrical power at the low voltage distribution level of the grid hierarchy, in real-time. So far, there is limited experience from pilot projects and field studies that could guide design and operation of such regional markets (Hatziargyriou *et al.* 2007; Blaabjerg *et al.* 2006). Most existing "smart grid" projects rely on intelligent devices and automation technology (Amin & Wollenberg 2005) to facilitate or even automate energy management at both consumer and generator sites, but they do not effectively address the interactions between the technology and the markets in which they are to operate. An interesting counterexample is (Vytelingum *et al.* 2010), which analyzes the motivation and social-welfare effects of individual adoption of small-scale energy storage on a national grid. The California energy market breakdown in 2000 (Joskow & Kahn 2001; Borenstein, Bushnell, & Wolak 2002) is an example of the problems that can occur if potential strategic, competitive or collusive behavior of market participants is not sufficiently accounted for in the design of such markets.

For these reasons, we propose and describe a competitive simulation environment that uses a market-based management structure for a local energy grid, designed to mirror reality fairly closely. This simulation environment would challenge research teams to create broker agents, or possibly agent-assisted decision support systems for human operators, that could operate effectively and profitably in direct competition with each other. Teams will thereby contribute to development of reliable and efficient automation technologies for efficient energy trading on the retail customer level. At the same time they will be challenged to exploit the structure of the market, and that structure will be adjusted periodically to defeat counterproductive strategic behaviors. The result will be a body of valuable research data that can guide energy policy, along with a much higher degree of confidence that such a mechanism can be safely introduced into operating energy systems.

Related work

The U.S. National Institute of Standards and Technology (NIST) recently published the first draft of a "Smart Grid Interoperability Standards Roadmap" (von Dollen 2009). It defines a simplified domain model for a future smart grid with identified "Distribution", "Market," and "Customer" domains being in the core of the overall model. Furthermore a list of prioritized actions for the fast transformation of the current infrastructure into a smart grid is provided. Highest priority, according to NIST, are Demand Response and consumer energy efficiency measures. In particular they state that *"Market information is currently not available to the customer domain. Without this information, customers cannot participate in the wholesale or retail markets. In order to include customers in the electricity marketplace, they need to understand when opportunities present themselves to bid into the marketplace and how much electricity is needed."*

The German industry group BDI has published a technology roadmap that describes the transition from the current energy infrastructure into a so called "Internet of Energy" (Block *et al.* 2008) on a timeline from 2009 to 2020. According to this roadmap, regional energy markets, virtual power plants based on micro Combined Heat and Power (CHP) turbines, as well as Demand Side Management (DSM) technologies will be mainstream by 2015. One of the key challenges identified is the development of *"applications and services implementing the coordination of the energy grid on the economic level"* in a sense that the technical infrastructure will be in place but smart coordination and operation strategies are yet to be developed.

Electricity production and distribution systems are complex adaptive systems (Miller, Page, & LeBaron 2007) that need to be managed in real time to balance sources and loads of an electricity grid. Electricity markets are undergoing a transition from centrally regulated systems to decentralized markets (North *et al.* 2002). The California energy market debacle (Borenstein, Bushnell, & Wolak 2002) and the recent collapse of Enron challenge the wisdom of deregulating the electricity industry, and have demonstrated that the success of competitive electricity markets crucially depends on market design, demand response, capacity reserves, financial risk management and reliability control along the electricity supply chain.

Agent-based modeling and simulation, especially using the methods of Agent-based Computational Economics (ACE) (Tesfatsion 2002), has emerged over the last few years as a dominant research tool of the energy sector. For instance, the Electricity Market Complex Adaptive Systems Model (EMCAS) electric power simulation is an agent simulation that represents the behavior of an electric power system and the producers and consumers that work within it (North *et al.* 2002). Sueyoshi and Tadiparthi (Sueyoshi & Tadiparthi 2008) have developed MAIS, an agent-based decision support system for analyzing and understanding dynamic price changes for the U.S. wholesale electricity market before and during the California energy crisis. A large scale simulation of interrelated German energy markets was developed by (Veit, Weidlich, & Krafft 2009), and (Sun & Tesfatsion 2007) use ACE to study U.S. wholesale power market designs. A nice review of agent-based simulation tools for energy markets can be found in (Zhou, Chan, & Chow 2007).

Over the last decade competitions are becoming increasingly prevalent in the research world. The current Trading Agent Competitions use a multi-year competition format to study trading in simultaneous online markets (TAC Classic) (Wellman, Greenwald, & Stone 2007), operation of a three-tier supply chain (TAC SCM) (Collins, Ketter, & Sadeh 2010), trading of search keywords for advertising purposes (TAC AA) (Jordan *et al.* 2009), and the operation of online exchanges (TAC CAT) (Niu *et al.* 2010).

Competition scenario

The main goals of the TAC Energy competition are (i) to provide a competitive testbed for the development and validation of a market structure for managing electrical power distribution in a local grid, (ii) to spur research and development on intelligent agents and decision support systems that help automate decision processes in such markets, and (iii) to ease knowledge transfer between research and application by providing a testing environment that closely resembles reality. The entities competing in this market will broker electrical power in a local energy grid that contains a mix of intermittent energy sources along with residential, commercial, and industrial demands.

The competition is focused on the role of a retail "energy broker," represented by a trading agent. In reality, such brokers could be energy retailers, municipal utilities, cooperatives, or in some cases large utilities. Within the competition, brokers offer tariff contracts to end customers (e.g. households, small and medium enterprices, owners of electric vehicles), who are attracted or deterred by the respective tariff conditions. Tariff conditions may include flat prices, time of use prices, peak prices, fully-dynamic prices, etc., along with inducements such as sign-up bonuses or penalties for early abandonment. In addition to "classical" tariff contracts for energy consumption, a broker can also sell "energy production" tariffs to end customers who wish to sell solar or wind power, as well as "balancing" tariffs for operation of decentralized energy storage capacity (batteries) or energy sources such as a CHP plant that feeds power into the grid, and is at least partially controllable by the grid operator.

Another type of energy consumer is a Plug-in Electric Vehicle (PEV). Owners of PEVs may be offered tariff contracts that have seperate, time dependent prices for charging the vehicle (consuming energy) and for feeding energy back into the grid (effectively producing energy). PEV customers are relatively large energy consumers during their charge cycle but might decide to discharge some of their stored energy at their own discretion if prices are sufficiently attractive.

On the tactical level (planning horizon: weeks – months) brokers have to develop portfolios of consumer, producer and PEV contracts. On the operational level (planning horizon: hours – days) brokers have to balance the fluctuating energy demands of their contracted consumers against the actual output of their contracted energy producers. Differences can be compensated ahead of time by setting prices for price-sensitive consumers and producers, by buying or selling power in the wholesale "energy exchange" market, and in real time through contracted balancing capacity or as a last resort through high-priced gas turbine "spinning reserves".

The competition is designed to model most of these challenges as close to reality as possible while keeping computational and technical complexity manageable. In particular we make the following assumptions:

1. Within the simulated region, we ignore grid constraints (line capacity limitations), i.e. power flows within the region are unconstrained. Local distribution grids are typically overdimensioned with respect to their line capacities, thus this assumption is not a strong restriction.
2. The point of common coupling (PCC) between the simulated distribution grid and the higher level transmission grid has a maximum capacity for power inflow and outflow. A specialised agent that serves as a "liquidity provider" on the regional energy spot market, and is able to arbitrage with the national energy spot market, has to obey these technical limits.
3. Power factor effects (phase shifts between voltage and current) are not taken into account. Modeling these effects would possibly influence broker decision making, but is out of scope at this time.
4. Power distribution and transformation losses are ignored. In the real world these losses range from 3% to 6% (Department of Energy 2006). These losses are more or less constant within a distribution grid and identical for all grid participants.
5. Two kinds of energy producers are distinguished. One kind (photovoltaic arrays, wind turbines) produce power when active, under control of their respective owners. The second kind (PEV batteries, some CHP units), along with some loads (e.g. domestic water heaters) is "controllable" and may be switched on or off, or have its capacity adjusted remotely within its contracted range.
6. In addition to remotely controllable generators and loads, some portion of supply and demand (such as charging and discharging of PEVs) can be controlled by voluntary or automated means in response to price signals.
7. Technical load balancing (i.e. the real time operations of the local distribution grid) is accomplished by the network operator using a combination of broker-contracted controllable supply and demand, and spinning reserves.
8. The simulation will model time as a series of discrete "timeslots" rather than as continuous time.
9. Energy production and consumption *within* a timeslot is assumed constant. This means that balancing power demand for a timeslot is calculated as the difference of the sum of generation and the sum of consumption for that timeslot and not as the instantaneous difference between the two timeseries.

In order to expose broker agents to tactical and operational decision making while keeping complexity under control, the competition scenario proceeds through a series of alternating *contracting* and *execution* phases. Both phases are described in more detail in subsequent sections.

To enhance realism of the scenario, we will drive the simulation with real historical data on generation, consumption, and weather information, along with a model of preferences of potential customers derived from customer surveys and pilot projects. One source of such data series is the German MeRegio project, a smart grid project that is implementing a combination of advanced grid control systems and innovative real-time pricing tariffs (Hirsch *et al.* 2010). A pilot region for MeRegio is the area around Freiamt, which contains a range of different distributed renewable energy generation facilities in combination with households and small and medium enterprises (SMEs) that are currently equipped with demand side management devices allowing them to flexibly react to price signals from the distribution grid.

With historic consumption and generation data collected from a region like this, the proposed simulation environment exposes the broker agents to the challenge of managing virtual consumers and generators, which exhibit realistic energy consumption and generation patterns based on the history data.

Contracting phase

On the simulation timeline, a contracting phase represents a short period of time (perhaps 60 seconds of real time). During this phase, broker agents may acquire capacity from local producers and sell energy to local customers as depicted in Figure 1.

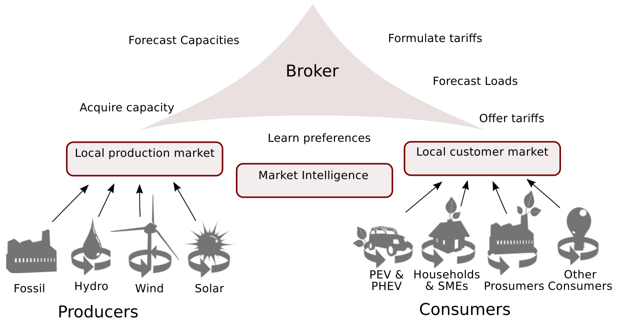

Figure 1: Contracting phase

To build profitable portfolios, brokers must estimate and reason about consumer and producer preferences in order to design appropriate tariffs. They will need to estimate future consumer and generator behavior to build a portfolio that has well-balanced demand and supply over time. In addition, they will need to include a reasonable proportion of remotely-controllable sources and loads to avoid paying the network operator for expensive balancing power. These are controlled during execution not by individual brokers, but by the network operator, who is finally responsible for balancing the grid.

Commonly, companies delegate the tasks of determining customer preferences and estimating business potential for new products (tariffs) to their marketing departments, or they outsource them to specialized service providers. Within the competition scenario, brokers may request such information from the *market intelligence* service. This service also provides brokers with historic supply and demand time series for producers and consumers under contract. With these

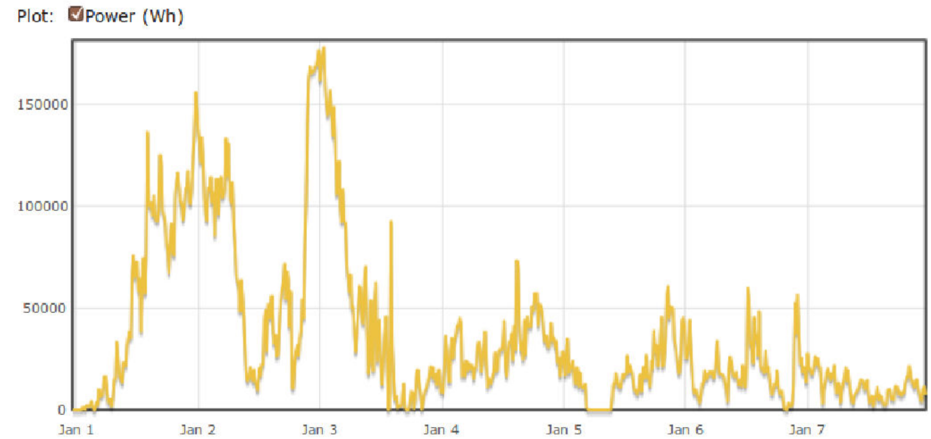

Figure 2: Sample wind turbine generation timeline as provided by the market intelligence service.

time series at hand, a broker will be able to estimate aggregate capacity over time. Figure 2 shows an example of such a historic time series for a wind turbine with a nominal capacity of 150kW.

Negotiating tariffs Tariffs are contracts that can be accepted or not by anonymous energy consumers and producers. The problem faced by broker agents in a competitive market is how to know whether a particular tariff will "sell." In the real world, firms are continually bidding against each other, attempting to attract the most "desirable" customers with their offerings. In the simulation, tariff offers are made in "rounds," and the number of rounds $|\mathcal{R}|$ is indeterminate to prevent "sniping" attacks. In each round $r \in \mathcal{R}$, agents are permitted to add or withdraw tariffs from their current offerings, resulting in a set of tariffs $\mathcal{U}_r$ for round r. The market intelligence service then runs a customer preference model to allocate customers to offered tariffs. Each agent is then provided with the number of customers who would agree to each of their offered tariffs, and they may then query the market intelligence service for predicted "demand profiles" for the projected customer base associated with each of their currently offered tariffs. These are simply aggregated time series for the set of customers who currently prefer the individual tariffs. At the end of the last round, no more offerings may be made, and brokers are charged a fee for each concurrently offered tariff. In other words, in each round r, a set of tariffs $\mathcal{U}_{b,r}$ is offered by broker b. If the fee for offering a tariff is p^{fee}, then the total tariff fee for the current contracting cycle will be

$$p_b^{\text{fee}} = p^{\text{fee}} \max_{\mathcal{R}}(|\mathcal{U}_{b,r}|), \forall r \in \mathcal{R}. \tag{1}$$

At the end of the last round, all currently-offered tariffs will be available for inspection by all agents through the market intelligence service.

Execution phase

During an execution phase (see Figure 3), each broker must manage supply and demand across its portfolio, by buying and selling energy in the regional exchange and by adjusting prices, over at least seven consecutive simulated days. Besides strong diurnal effects, energy demand also differs significantly between working days and weekends. The length of seven days ensures an inclusion of both type of days within each execution phase. The exact length of an execution phase is not revealed in advance, to reduce boundary effects.

The broker needs to ensure that total energy demands and supplies of the customers and generators in its portfolio are balanced for each time period through the whole execution phase. Deviations between production and consumption might still occur but will be charged an (expensive) balancing power fee. In this context, balance between supply and demand during a timeslot s means that

$$e_{\text{im}}(b, s) + \sum_{j=1}^{|\mathcal{G}_b|} e_j(s) = e_{\text{ex}}(b, s) + \sum_{i=1}^{|\mathcal{C}_b|} e_i(s) \tag{2}$$

where $\mathcal{G}_b$ is the set of contracted power producers for agent b, $\mathcal{C}_b$ is the set of contracted consumers for b, $e_j(s)$ is the total energy produced by generator j, $e_i(s)$ is the total energy used by consumer i, $e_{\text{im}}(b, s)$ is power imported (purchased) by broker b from the regional exchange for delivery during timeslot s, and $e_{\text{ex}}(b, s)$ is power exported (sold) by broker b into the regional exchange. Note that $e_j(s)$ and $e_i(s)$ can include an arbitrary portion of contracted balancing power.

A broker's portfolio (i.e. the set of contracts) remains stable throughout an execution phase, but the overall energy demand and supply within the portfolio is volatile over time. This behavior is simulated using historical data.

Collecting information and predicting the future As during the contracting phase, a broker may request historic time series data for the seven preceding days (i.e. the approximate length of one complete execution phase) from the market intelligence service for all generators and consumers currently under contract. With this historic data series at hand a broker will be able to build its own prediction model for future energy consumption and production of its portfo-

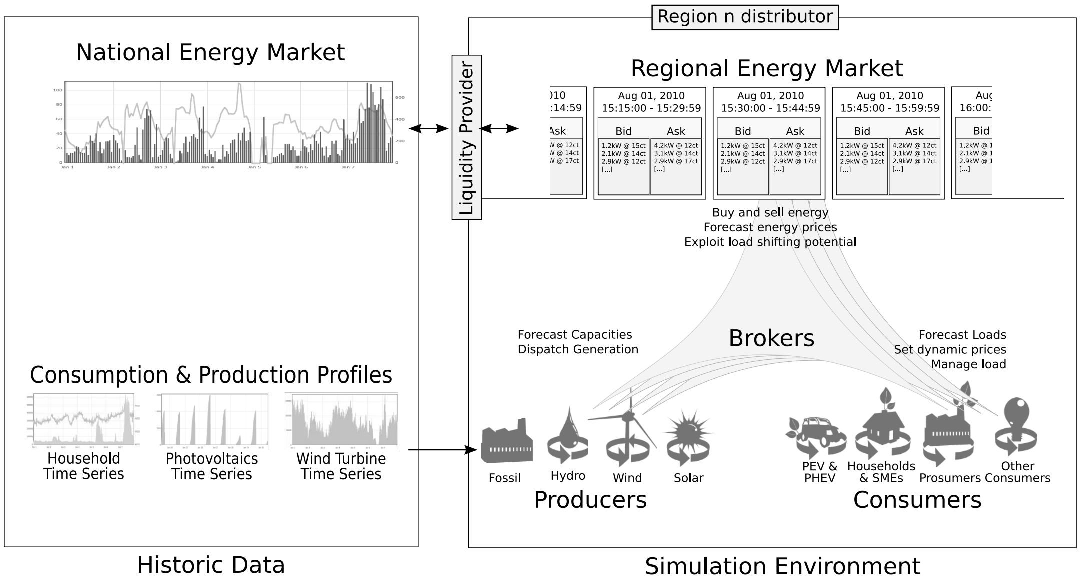

Figure 3: Execution phase: Brokers manage their portfolios and trade in the regional market.

lio, in order to be able to detect and address likely future imbalances.

In general, retrieval of future time series data from the market intelligence service is not permitted, with one exception: For intermittent generators such as photovoltaics or wind turbines, the estimation of future output solely based on historic time series data is unrealistic. Predictions for such sources are usually based on weather forecasts as described for example in (Sanchez 2006).

In order to shield brokers from having to model weather forecasts, and also because forecasts for specific generators as input for the competition are usually not publicly available[1] the approach for this competition is to permit future time series data lookups only for *intermittent* generators. In order to accurately model the problem brokers must solve, these future time series will be artificially distorted to exhibit approximately the level of accuracy that might be achieved using the best available weather forecasts (see (Ahlert & Block 2010) for background).

Based on (i) the historic generation schedules of "predictable" generators (e.g. micro turbines or CHP plants), (ii) the historic consumption schedules of the consumers under contract, and (iii) the forecasted generation schedules of intermittent generators, a broker will have to estimate future energy production and consumption schedules for its portfolio as visualized in Figure 4. Note how the uncertainty for the expected demand and supply in time slots far into the future is higher than for those near to the current time slot. In Figure 4(a) the maximum expected overall generation capacity of broker b in time slot s_{n+5}, $e'_g(b, s_{n+5})$ is much lower than the expected overall load $e'_c(b, s_{n+5})$. But as the mean absolute percentage errors (MAPEs) for both numbers are high (indicated as gray boxes), the accuracy of this prediction is low. The MAPE for the overall consumption stems from the demand forecasting model the broker has to build on its own. The MAPE for the overall generation stems in part from the artificial distortion of future production data, and in part from the broker's prediction model for forecasting non intermittent production capacities like e.g. CHP engines or micro gas turbines. 120 minutes later (Figure 4(b)), the expectation values for supply and demand remained unchanged but the uncertainty has decreased. At this point the broker is able to predict an excess demand situation for the time slot with confidence and thus can introduce appropriate countermeasures. In this case it decided to acquire additional energy for time slot s_{n+5} from the regional energy exchange as indicated in the Figure. An alternative would be to adjust energy production and supply within its portfolio as described in the following section.

Adjusting energy demand and supply For each time slot s, each broker a must balance expected supply and demand. Expected demand is the sum of the expected loads $e'_i(s)$ of each consumer i in the the consumer portfolio $\mathcal{C}_b$ during time slot s:

$$e'_C(b, s) = e_{\mathrm{ex}}(b, s) + \sum_{i=1}^{|\mathcal{C}_b|} e'_i(s) \tag{3}$$

Expected supply is total expected production capacity of all generators j within portfolio $\mathcal{G}_b$:

$$e'_g(b, s) = e_{\mathrm{im}}(b, s) + \sum_{j=1}^{|\mathcal{G}_b|} e_j(s) \tag{4}$$

In addition, the broker will have some amount of contracted balancing load $\epsilon_c(b, s)$ and balancing generation capacity $\epsilon_g(b, s)$. These amounts may be subtracted from load or production by the grid operator during timeslot s to achieve

[1] Such forecasts are provided by specialized companies that charge significant fees.

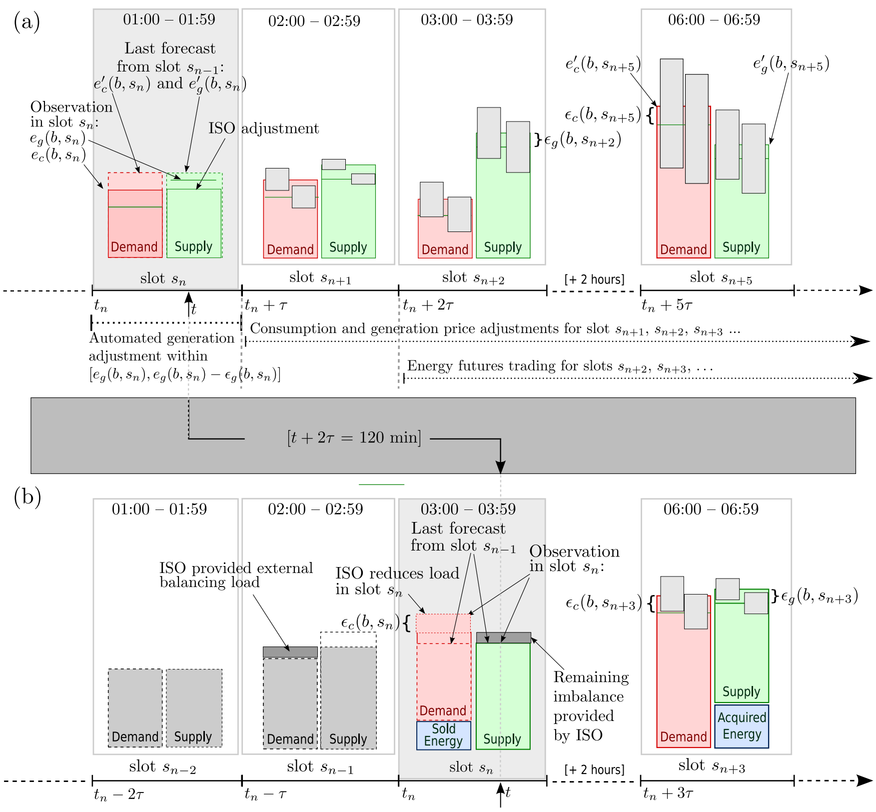

Figure 4: Broker's total energy demand and supply as anticipated at a particular point in time (a), and again two hours later (b).

exact balance. Therefore, as long as $e'_c(b,s) - \epsilon_c(b,s) \leq e'_g(b,s)$ and $e'_g(b,s) - \epsilon_g(b,s) \leq e'_c(b,s)$ then time slot s is in balance, or at least expected to be so.

In Figure 4(a), we can see that the forecasted overall consumption of broker b deviated from the actual consumption $e_c(b,s_n)$. But as the difference between $e_c(b,s_n)$ and $e_g(b,s_n)$ was smaller than the production balancing capacity $\epsilon_g(b,s_n)$, the network operator automatically shut down a portion of the balancing capacity such that overall demand and supply for timeslot s_n was rebalanced. A broker agent cannot directly affect production or consumption in the current time slot s_n.

For time slot s_{n+1} in Figure 4(a), overall demand was forecasted to be within range of the available production capacities even when taking uncertainty (indicated as grey boxes) into account. In other words $e'_g(b,s_{n+1}) - \epsilon_g(b,s_{n+1}) \leq e'_c(b,s_{n+1})$. After 2τ simulation time elapsed (Figure 4(b)), the real consumption in this time slot turned out to be even lower than was predicted. This means that even after the simulation environment reduced the generator's internal balancing power capacity to its minimum level, the overall production still exceeded the overall consumption. In this case *external balancing power* (e.g. some large pumped-storage power plant outside the broker's portfolio) had to absorb the excess generated energy. In the energy industry this type of balancing power is usually called an "ancillary service" and its utilization is billed to the broker at a defined (high) price.

In slot s_{n+2} in Figure 4(a), the broker forecasts a significant difference between overall production and overall consumption. Internal balancing capacity is likely to be insufficient for leveling the expected difference. In order to avoid the (expensive) utilization of external balancing power, broker a can use its contracted pricing power to try to encourage (i) some or all of its consumers to increase their demand, or (ii) some or all of its producers to reduce their production. Technical adjustments initiated by the broker (e.g. a remote activation of loads at consumer premises) is not allowed within the competition. But a consumer's energy consumption $e_c(i,s)$ is subject to the energy consumption price for this consumer in a time slot s, which is defined as $p_c(i,s)$. We define

$$\hat{e}_c(i,s_{n+2}) = e'_c(i,s_{n+2},p_c(i,s_{n+2})) \tag{5}$$

as the predicted load for consumer i in time slot s_{n+2}, given price $p_c(i,s_{n+2})$. If the broker changes the underlying consumption price to $p'_c(i,s_{n+2})$ the forecasted consumption of this consumer is expected to increase as

$$\hat{e}'_c(i,s_{n+2}) = e'_c(i,s_{n+2},p'_c(i,s_{n+2})) \tag{6}$$

The ratio of demand change to price change

$$PE_i = \frac{\hat{e}_c(i,s,p) - \hat{e}_c(i,s,p')}{p - p'} \tag{7}$$

is called the "price elasticity" for consumer c. Price elasticities will have to be modeled within the different consumer agents provided by the competition environment, following empirical findings on price elasticity as described for example in (Spees & Lave 2008; Siddiqui, Bartholomew, & Marnay 2004).

Some producers in the broker's portfolio (such as PEV batteries that can be discharged into the grid) might have agreed to flexible pricing as well, and therefore their output will be sensitive to price in a similar way. In other words, the power generation capacity of broker b in time slot s, $e_g(b, s)$, is likely to decrease if the generation price $p_g(j, s)$ for a producer j is changed to $p'_g(j, s)$, assuming $p'_g(j, s) < p_g(j, s)$. We also assume that the internal balancing power capacity $\epsilon_g(b, s)$ and $\epsilon_c(b, s)$ will remain unchanged, assuming that the balancing portion of the tariff contracts offered by agent b are not price-sensitive.

Buying or selling futures on the energy market The readjustment of energy prices for consumers and generators as well as the advance reservation of (partial) generator capacity as balancing power reserves are two possibilities to level out a broker's portfolio over time. A third option is to buy missing or to sell excess capacities on the energy market. Within the competition this market is modeled as a continuous double auction with uniform pricing and thus resembles the prevalent mechanism design in place for energy spot market trading in Europe and North America (Meeus & Belmans 2007). On this market standardized energy futures are traded. An energy future is a binding commitment to consume or to produce a defined amount of energy (e.g. 1kWh) within a defined future time slot (e.g. Aug 01, 2007, 03:00 – 03:59) at a defined price (e.g. 0.20 $/kWh). In order to buy or sell energy futures, a market participant sends bid or ask orders to the energy market, which then clears (matches) all incoming bids and asks at a uniform price determined according to the the maximum turnover needed principle (see e.g. (EEX 2008) for a detailed description of the mechanism).

In addition to the brokers, the regional market includes a special "liquidity provider" to represent the point of common coupling (PCC) between the simulated region and the national grid. It can buy energy at the national market and transfer it via the PCC to the simulated region and vice versa. Thus the liquidity provider serves as an arbitrage agent that levels prices of the regional and the national energy market and constitutes an *explicit market coupling* (Meeus & Belmans 2007).

Conclusion and future work

We have described a competitive simulation of a market-based management structure for local energy grids. It would closely model reality by bootstrapping the simulation environment with real historic load, generation, weather, and consumer preference and usage data. The competition challenge research teams from around the world to write autonomous agents, or agent-assisted decision support systems for human operators (Varga, Jennings, & Cockburn 1994), that could operate effectively and profitably in direct competition with each other, while also continuously balancing energy supply and demand from their portfolios. Teams would also be challenged to exploit the structure of the market, and that structure would be adjusted periodically to defeat counterproductive strategic behaviors. The result would be a body of valuable research data, along with a much higher degree of confidence that such a mechanism could be safely introduced into operating energy systems.

Agents in the proposed market simulation would act as retail brokers, purchasing power from distributed sources and from regional energy exchanges, and selling power to consumers and exchanges. These agents must solve a set of complex supply-chain problems in which the product is infinitely perishable, and the environment is subject to high variability and uncertainty (e.g. weather effects, equipment and network outages) and limited visibility. They will operate in a dynamic network at multiple timescales, from negotiating long-term contracts with energy sources and tariffs for customers that balance supply and demand in expectation, to day-ahead spot-market trading, to real-time load balancing. They must deal with individual customers and suppliers, while at the same time aggregating the preferences of large groups of customers into market segments for tariff offerings. They must predict supply and demand over monthly, quarterly, and yearly timescales as they develop their portfolios of supplier and customer relationships, and over hours and minutes as they adjust dynamic prices and trade in the spot market in order to maintain real-time balance in the grid.

We expect the primary result of this study to be twofold. First a clear understanding for policymakers of the capabilities and limitations of open market structures for management of future energy networks that include a variety of distributed sources, including electric vehicles. Second, competitive, agent-based automation strategies are developed that may provide valuable decision support and automation options for retail market operation. This simulation will allow such structures to be evaluated in a risk-free environment under a variety of real-world conditions ranging from normal to extreme. The competitive design will effectively uncover potential hazards of proposed market designs in the face of strategic behaviors on the part of the participating agents. The likely effects of various dynamic pricing approaches for consumers and electric vehicle charging can be evaluated. Complex preference models will be developed that have three important properties: attractive to consumers, attractive to brokers, and give brokers sufficient flexibility to balance loads in expectation and in real time. Methods will be developed for charging large numbers of electric vehicles in ways that are both technically feasible and economically attractive to consumers, and that take advantage of the balancing capacities of vehicles.

A more complete description of the TAC Energy scenario is available as (Block *et al.* 2009).

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