Smart Grid Economics:
Policy Guidance through Competitive Simulation

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ERIM REPORT SERIES *RESEARCH IN MANAGEMENT*	
ERIM Report Series reference number	ERS-2010-043-LIS
Publication	December 2010
Number of pages	16
Persistent paper URL	http://hdl.handle.net/1765/21307
Email address corresponding author	wketter@rsm.nl
Address	Erasmus Research Institute of Management (ERIM) RSM Erasmus University / Erasmus School of Economics Erasmus Universiteit Rotterdam P.O.Box 1738 3000 DR Rotterdam, The Netherlands Phone: + 31 10 408 1182 Fax: + 31 10 408 9640 Email: info@erim.eur.nl Internet: www.erim.eur.nl

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ABSTRACT AND KEYWORDS	
Abstract	Sustainable energy systems of the future will need more than efficient, clean, low-cost, renewable energy sources; they will also need efficient price signals that motivate sustainable energy consumption as well as a better real-time alignment of energy demand and supply.
Free Keywords	energy trading, market simulation, market design, multi-agent systems, complex networks, trading agent competition
Availability	The ERIM Report Series is distributed through the following platforms: Academic Repository at Erasmus University (DEAR), DEAR ERIM Series Portal Social Science Research Network (SSRN), SSRN ERIM Series Webpage Research Papers in Economics (REPEC), REPEC ERIM Series Webpage
Classifications	The electronic versions of the papers in the ERIM report Series contain bibliographic metadata by the following classification systems: Library of Congress Classification, (LCC) LCC Webpage Journal of Economic Literature, (JEL), JEL Webpage ACM Computing Classification System CCS Webpage Inspec Classification scheme (ICS), ICS Webpage

Smart Grid Economics: Policy Guidance through Competitive Simulation

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Sustainable energy systems of the future will need more than efficient, clean, low-cost, renewable energy sources; they will also need efficient price signals that motivate sustainable energy consumption as well as a better real-time alignment of energy demand and supply.

We know how to build "smart grid" [1] components that can record energy usage in real time and help consumers better manage their energy usage. However, this is only the technical foundation. Variable energy prices that truly reflect energy scarcity can motivate consumers to shift their loads to minimize cost, and for producers to better dispatch their capacities [12]. This will be critical to the effort to develop a more sustainable energy infrastructure based on increasing proportions of variable-output sources, such as wind and solar power. Unfortunately, serious market breakdowns such as the California energy crisis in 2000 [4] have made policy makers justifiably wary of setting up new retail-level energy markets.

The performance of markets depends on economically motivated behavior of the participants, but proposed retail energy markets are too complex for straightforward game-theoretic analysis. Agent-based simulation environments have been used to study the operation of wholesale power markets [19], but these studies are not able to explore the full range of unanticipated self-interested or destructive behaviors of the participants. Smart grid pilot projects [9], on the other hand, are limited in their ability to test system dynamics for extreme situations. They also lack the competitiveness

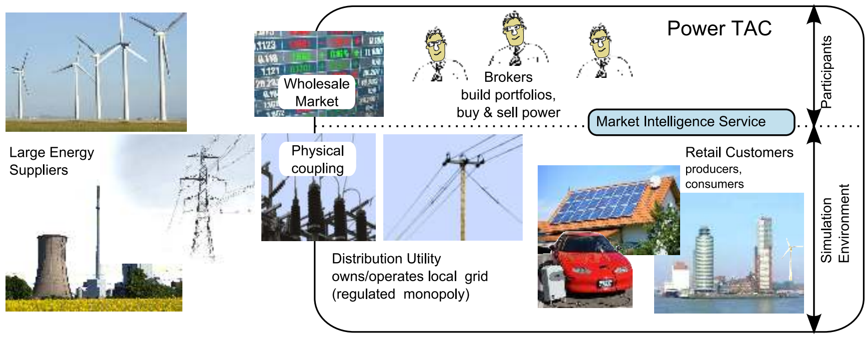

Figure 1: Major elements of the Power TAC scenario.

of open markets, because a single project consortium typically controls and optimizes the interaction of all parts of the pilot regions. Therefore, we are developing an open, *competitive* market simulation platform that will address the need for policy guidance based on robust research results on the structure and operation of retail power markets. These results will help policy makers create institutions that produce the intended incentives for energy producers and consumers. They will also help develop and validate intelligent automation technologies that will allow effective management of retail entities in these institutions.

We call this vision the *Power Trading Agent Competition* because it is an example of a Trading Agent Competition[1] applied to electric power markets.

Background

The power grid infrastructure today is organized in a strict hierarchy: A few centralized control centers manage relatively few large power plants and schedule their production according to energy demand forecasts. These typically come from day-ahead wholesale markets and long-term contracts, influenced by weather forecasts and synthetic load profiles, i.e. average historic consumption time series for different consumer groups. Anticipated shortages and surplus are traded on wholesale markets among regions, subject to capacity limitations of cross-regional grid inter-connections.

The need to reduce carbon emissions and the decreasing availability of fossil energy resources is leading to increasing reliance on variable-output

[1]see www.tradingagents.org

sources such as wind and solar, but effective use of these resources will require that energy users adapt to the availability of sustainable power. In addition, many households and businesses are installing small, distributed and variable-output renewable energy sources. These are connected to the medium and low voltage distribution grid, and are outside the control of centralized management. In parallel, smart metering equipment and demand side management devices (DSM) are being installed at customer premises to help them monitor and actively manage their energy usage. Consequently, customer demand elasticity will increase and demand predictions via synthetic load profiles will become more difficult, especially as time-of-use and real-time energy price tariffs are introduced.

The U.S. National Institute of Standards and Technology (NIST) recently published the first draft of a Smart Grid Interoperability Standards Roadmap [24] Highest priority, according to NIST, are demand response and consumer energy efficiency measures. In particular, they argue that without market information, customers cannot effectively participate in wholesale or retail energy markets.

Similarly, in October 2009 the EU Commission announced the Strategic Energy Technology Plan (SET Plan) [8] along with a draft technology roadmap. One of the priority actions mentioned in this roadmap is the development of so called "smart cities" that efficiently and intelligently manage local energy production and consumption[2].

Multi-Agent Modeling and Competition

Electricity production and distribution systems are complex adaptive systems that need to be managed in real time to balance production with demand. Electricity markets are undergoing a transition from centrally regulated systems to decentralized markets [11]. These transitions are very risky since we do not have sufficient experience in setting up decentralized energy systems and predicting their effect on the economy. We have observed in recent history that failures in designing such systems can cause major damage. The California energy market [4], and the 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. Therefore, it is very important to thoroughly test system and market design

[2] see e.g. http://www.amsterdamsmartcity.com

proposals in a risk free simulated environment before deploying these ideas into the real world.

Although traditional optimization and simulation tools continue to provide many useful insights into market operations, they are limited in their ability to reflect the diversity of agents participating in these markets, each with unique business strategies, risk preferences, and decision processes. Partly to address these shortcomings, agent-based modeling and simulation has emerged over the last few years as a dominant tool for study of energy markets. 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 [18]. Sueyoshi and Tadiparthi [20] describe 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 number of studies have used Agent-based Computational Economics (ACE) [22] methods to study electrical wholesale power markets, for example [17, 25, 21].

All of these studies are focused primarily on wholesale power markets, rather than retail markets. Because these simulations are built by individual research groups, their ability to test the full range of (potentially destructive) strategic behaviors is limited by the imagination of a small group of researchers. The competitive simulation approach extends ACE by constructing a rich simulated market environment in which one of the agent types (the retail energy broker in the case of Power TAC) faces competition from other agents of the same type. As in the Trading Agent Competition for Supply Chain Management (TAC SCM) [7], we then invite independent research groups to implement their own agents to operate in that role, and pit them against each other in the simulated market. This provides a much more rigorous test of the market design, and produces deep knowledge of strategy options and decision procedures for these agents. Examples include the empirical game theory work of Jordan et al. [10] or the economic-regime work of Ketter et al. [14].

Competition Scenario

The major elements of the Power TAC scenario are shown in Figure 1. Competing teams will construct trading agents to act as self-interested "brokers" that aggregate energy supply and demand with the intent of earning a profit. In the real world, brokers could be energy retailers, commercial or munic-

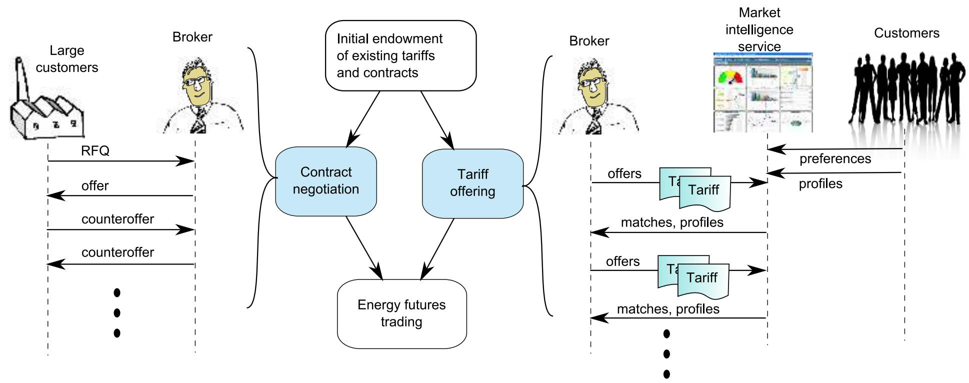

Figure 2: Contracting process. Tariff offerings proceed in parallel with individual contract negotiation.

ipal utilities, or cooperatives. Brokers will buy and sell energy through contracts with retail customers (households, small and medium enterprises, owners of electric vehicles), and by trading in a wholesale market that models a real-world market such as the European or North American wholesale power markets. Brokers compete with each other trying to attract customers by offering *tariff* contracts to a population of anonymous small customers (households, small businesses), and by negotiating individual contracts with larger customers (such as major manufacturing facilities, or greenhouse complexes with many Combined Heat and Power (CHP) units). Contract terms may include fixed or varying prices for both consumption and production of energy, along with other incentives such as rebates for energy conservation, or even signup bonuses or early-withdrawal penalties. Separate contracts may be offered for charging electric vehicles, which could limit charging during high-demand periods, or even offer to pay the customer for feeding energy back into the grid at certain times. Variable prices may follow a fixed schedule (day/night pricing, for example), or they may be fully dynamic, possibly with a specified advance notice of price changes. Dynamic pricing could motivate some customers to invest in "smart" appliances that can receive price signals and adjust energy use to control costs.

The simulation is designed to model power markets primarily from an economic rather than from a technical viewpoint, and therefore we currently do not simulate the physical infrastructure.[3] In the future, we anticipate integrating the market simulation with a physical simulation in order to be

[3] A complete list of assumptions can be found in [3].

able to evaluate the technical feasibility of the market's energy allocation over time.

Broker agents are challenged to plan their activities over multiple timescales through a series of alternating *contracting* and *execution* phases. During a contracting phase (planning horizon: weeks to months), brokers have to build their portfolios of consumer, producer and electric vehicle customers by offering tariff contracts and negotiating individual contracts. During the subsequent execution phase (planning horizon: hours to days), brokers switch to the operational level, balancing the fluctuating energy demands of their contracted power consumers against the actual output of their contracted energy producers. Differences between supply and demand must be accommodated by purchasing or selling in the wholesale power market. Retail market dynamics thus influence the wholesale market and vice versa.

The simulation includes a range of customer models, including electric vehicles, CHPs, solar panels and wind turbines, and multiple models of private households, clustered by preference similarity. An important feature of these models is their responsiveness to price changes [2].

To enhance the realism of the competition scenario, it is designed to operate with either real historical data on generation, consumption, and weather information, or with stylized data, along with preference models for various classes of 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 [9].

Contracting phase

A broker's primary goal during the contracting phase is to develop a good-quality portfolio of tariff and individual contracts with customers who will sell or purchase power. The ideal portfolio is profitable and balanced, at least in expectation, over the period of the next execution phase. A secondary goal is to manage financial and supply/demand imbalance risks. For example, an agent will benefit from having reasonably-priced energy sources that can be expected to produce power when demand is expected to be highest within its load portfolio. Predictability is also important, and will generally improve both with volume and with a balanced portfolio of uncorrelated generation capacities and loads. Risk can be managed by acquiring uncorrelated sources and loads that can be expected to balance each other in real time, by acquiring storage capacity, by acquiring flexible generation capacities (balancing power), by selling variable-price contracts, and by trading

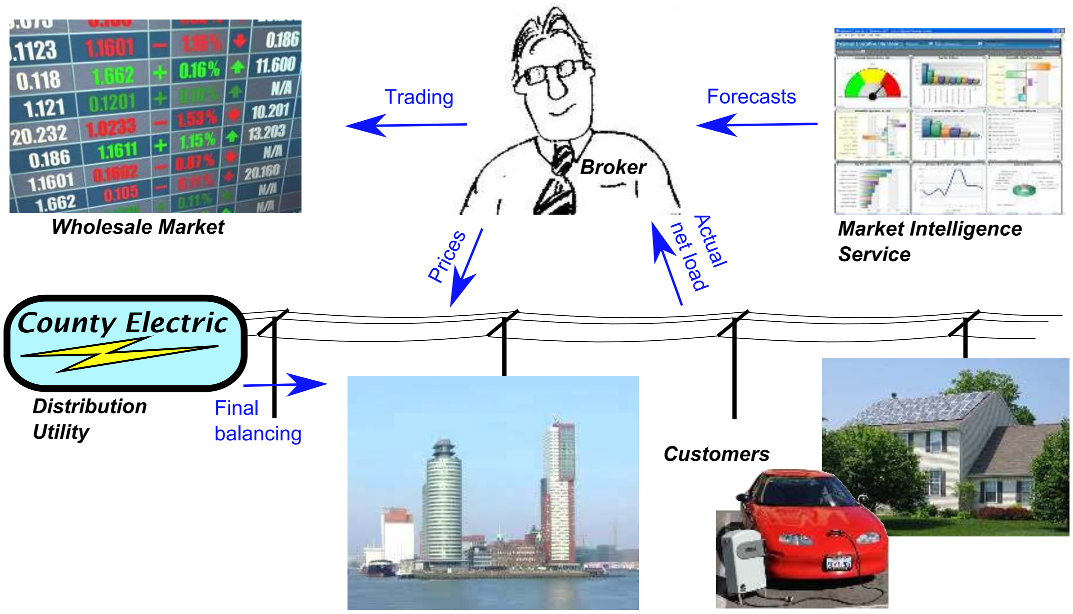

Figure 3: Entities and activities during an execution phase

futures contracts on the wholesale market.

On the simulation timeline, a contracting phase represents a short period of time (perhaps 60-120 seconds), during which brokers simultaneously negotiate over individual contracts and tariffs as depicted in Figure 2. Contract language allows brokers and their customers to express a variety of terms and conditions covering a range of domain concepts, including:

Time: including points in time, time intervals, periodicity (days, weeks, months, etc.), and temporal relationships (before, after, during, etc.). These terms can be used to specify contract duration, lead times for price change signals, and other time-related issues.

Energy: including amounts of energy produced or consumed, and rate of production or consumption (power). Contracts or tariffs may also specify amounts of power that can be remotely controlled, for example by shutting off a domestic water heater for 15 minutes every hour during peak demand periods. Such remotely-controllable sources or loads are collectively called *balancing capacity*.

Money: Agreements must specify payments to or from the customer based on time (one-time signup fee or bonus, fixed monthly distribution fees), or time and energy (fixed or variable prices for a kilowatt-hour).

Communication: contract award and termination, notification of price changes, availability of balancing capacity, etc.

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* (c.f. Fig. 2). The Market Intelligence Service also provides brokers with historic consumption time series for all consumers and producers under contract. With these time series, a broker will be able to estimate how much generation and consumption capacity will be available over time and whether its portfolio is well balanced.

Posted tariffs

Tariffs are offered 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 adjusting their tariff offers against each other, attempting to attract the most "desirable" customers with their offerings.

One way to simulate this process is to allow brokers to offer tariffs in multiple "rounds," with the number of rounds indeterminate to prevent strategic behavior of brokers. In each round agents are permitted to add or withdraw tariffs from their current offerings. The Market Intelligence Service then runs a customer preference model to allocate customers to offered tariffs. After each round, all brokers are 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.

Negotiated contracts

Individual contracts are negotiated through an RFQ process, initiated by large customers (producers and consumers of power), and proceeding through one or more rounds with broker agents that continue to be interested. The process ends when any party accepts the current contract, or when either the customer or all brokers choose to withdraw. In order to avoid overwhelming brokers with requests for individual contracts, the smallest entities that will engage in this process will be (simulated) large industrial, commercial, or government entities that consume or produce far more power than an individual household or small business.

Execution phase

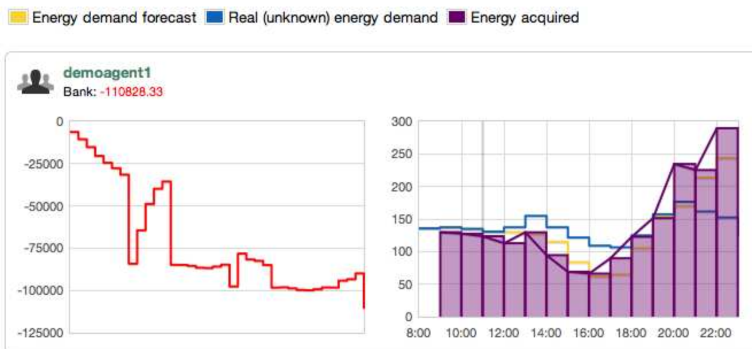

Figure 4: One agent's view during an execution phase.

At the end of the contracting phase, the agent has knowledge of its contract commitments. An execution phase (see Figure 3) simulates some period of time during which these contracts are in place, typically one to two weeks. Besides strong diurnal effects, energy demand also differs significantly between working days and weekends. The design ensures an inclusion of both type of days within each execution phase. The exact length of an execution phase is drawn from a random distribution but is not revealed in advance to the agents, to reduce undesirable end game effects within the competition. In this phase time is divided into discrete "timeslots" corresponding to the time units traded in the wholesale market.

At the beginning of each execution phase, broker agents are given an opportunity to request history and forecast data, to adjust their variable prices, and to trade in the wholesale market before the clock starts running. During this setup interval, energy can be traded for all timeslots.

Balancing supply and demand

After the setup period, agents may trade in the exchange and set variable prices at any time. At the end of each timeslot, the agent receives a performance report giving the supply and demand volume for each of its contracts and tariffs. For each future timeslot a broker must maintain a forecast of its total expected supply and demand. The Market Intelligence Service, for a fee, will provide forecasts based on historical production and consumption for most sources and loads, but since some renewable sources are weather-dependent, the actual future output of these generators is statistically distorted to simulate the inaccuracy of weather forecasts. Given this information, the agent's task is to adjust prices, and to trade in the wholesale market, in order to achieve expected balance. Deviations between production and consumption that exceed a broker's own balancing capacity will be charged an (expensive) balancing power fee from the Distribution Utility (DU, part of the simulation).

The DU has to ensure exact balance between supply and demand in real time. Any remaining imbalance across all broker portfolios will be balanced by the DU using its own resources ("spinning reserves") and charged to those brokers who are responsible for the residual imbalance.

Buying or selling futures on the energy market

In addition to adjusting prices and reserving some capacity for balancing, brokers have a third option for achieving balance between supply and demand. This is to buy or sell excess demand or capacity on the wholesale energy market. Within the simulation, prices in this market are stabilized by a special agent called a *liquidity provider*, which represents the Point of Common Coupling (PCC) between the simulated retail distribution grid and the transmission grid. It implements the supply price curve in the wholesale market, as well as the physical constraints of the PCC. Thus the liquidity provider serves as an arbitrage agent that levels prices of the retail and wholesale energy markets, and constitutes an explicit market coupling [16] between both markets.

Example

A prototype simulation models the execution phase, consisting of a server that models the market along with producers and consumers, and connected through the Internet to individual broker agents. These are given a portfolio of energy sources and loads they have to manage, and must sell or acquire energy on the wholesale market in order to achieve balance. The screenshot in Figure 4 shows the view of one agent at just before 11:00. At this point, we can see that the agent purchased less than the needed power for timeslots 12:00, 14:00, and 15:00, and more than needed in the 17:00 and 18:00 timeslots.

The problem the agent must solve is illustrated by the difference between the "forecast" and "demand" curves for the future. The agent sees only the forecast data; the simulator produces the forecast from the actual supply and demand data for the agent's portfolio artificially distorting the real demand in order to simulate uncertainty of real-life demand forecasts. Given these forecasts, the agent must acquire (or sell) enough energy, by trading in future timeslots, to achieve balance before each timeslot becomes the current timeslot.

Research value

Power TAC is designed to run as an annual competition, a model that has been very effective in stimulating research. The basic annual research cycle is shown in Figure 5. Each year, research groups build or update their agents and enter them in the competition. The competition is typically held in conjunction with a relevant major conference where participants can present their work, discuss what they have learned, and begin planning for the next competition cycle. After the competition, teams are encouraged to release their agent code, so all teams can design and run their own experiments using a range of broker behaviors and market design details. The results are published, and teams incorporate new insights into their agent designs for the following year. Each year, the simulation may be updated to add new challenges, and if necessary to tune the market designs and level of realism to enhance the relevance of the shared enterprise for both research value and policy guidance.

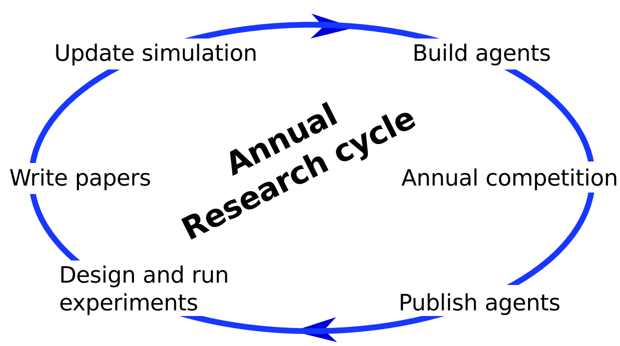

Figure 5: Annual research cycle for competitive simulation.

We will continuously evaluate and adapt the Power TAC design by asking the following three questions:

1. How adequate is Power TAC as a representation of the real world? For instance, we could compare pricing and load balance predictions between Power TAC and the real world from data available from the MeRegio project or other real-world studies.

2. How effectively does Power TAC support the research agenda of the participating teams? For instance, are teams effective at modeling preferences or price predictions using Power TAC?

3. How effective is Power TAC for public policy guidance? Do the suggested solutions provide new insights into real world policy generation?

The full specification and implementation is being prepared for the first competition competition in the summer of 2011 at the Internal Joint Conference for Artificial Intelligence in Barcelona.

Conclusions

Power TAC is a competitive simulation of retail electric power markets that provides a market-based management structure for local energy grids. It will challenge research teams from around the world to write autonomous agents, or agent-assisted decision support systems for human operators [23], that could operate effectively and profitably in direct competition with each other, while also continuously balancing supply and demand in a heterogenous customer portfolio. Teams will also be challenged to exploit the structure of the market, and that structure will be adjusted and fine-tuned after each competition tournament to defeat counterproductive strategic behaviors and to ultimately develop a set of competitively proven market rules. The result will be a body of valuable research data, along with a much higher degree of confidence that such a market mechanism could be safely introduced into real world smart grid systems. The competition will also produce a variety of thoroughly tested agent-based energy market trading strategies.

Competitions have been shown to be an effective way to spur innovation [13, 15]. We expect the primary result of this study to be 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, sustainable sources. 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. As a competitive real world testbed, Power TAC gives ample opportunities for scientists and practitioners from different disciplines to research and contribute to a variety of important challenges. The initial focus in Power TAC will be on modeling the behavior and strategies of the broker agents. Competing broker agents may be fully autonomous [5]. In future, we envision semi-autonomous, interactive versions of Power TAC [6] with human participants in the role of ultimate decision makers throughout the competitions. Modeling electric vehicles within the Power TAC platform is another field for future work. A goal in working with such interactive systems is to discover what types of decision support are most effective at raising the performance of human decision makers in fast-paced environments such as this.

Since the simulation environment and broker agents are subject to high variability, uncertainty and limited visibility, we can study the impact on system stability through exogenous shocks, such as power plant failure, and competition effects among broker agents. We can examine the effects of policy changes, such as taxes and incentives. We can research how rapid technical infrastructure changes affect the environment, and how we can balance these changes in real time. Ultimately, the test of relevance will be that the resulting research helps bring about a more sustainable energy future.

Acknowledgements

We thank the members of the TAC and E-Energy community for their valuable feedback on our design, and for the great help with the development of the Power TAC platform. Special thanks goes to Antonios Chrysopoulos, David Dauer, Joseph D'Costa, Sebastian Gottwalt, Yixin Lu, Adis Mustedanagic, Vedran Podobnik, Kang Puthyrak, Prashant Reddy, Daniel Schnurs, Andreas Symeonidis, and Manuela Veloso.

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