Market Design Test Environments

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***Abstract*—Power industry restructuring continues to evolve at multiple levels of system operations. At the bulk electricity level, several organizations charged with regional system operation are implementing versions of a Wholesale Power Market Platform (WPMP) in response to U.S. Federal Energy Regulatory Commission initiatives. Recently the Energy Policy Act of 2005 and several regional initiatives have been pressing the integration of demand response as a resource for system operations. These policy and regulatory pressures are driving the exploration of new market designs at the wholesale and retail levels. The complex interplay among structural conditions, market protocols, and learning behaviors in relation to short-term and longer-term market performance demand a flexible computational environment where designs can be tested and sensitivities to power system and market rule changes can be explored. This paper discusses the use of agent-based computational methods for the study of electricity markets at the wholesale and retail levels, and explores distinctions in problem formulation between these levels.**

Index Terms—**agent-based modeling, adaptive systems, power system simulation, power system economics, market design**

I. Introduction

The use of market-based approaches in electric system operations continues to mature. Rather than use actual systems as test beds for new market rules or regulatory policies, decision makers can use agent-based computational frameworks as safe environments within which to explore the potential effects of their actions. The abstract modeling of an electric system needs to cover the fuel, wholesale electricity, and retail electricity markets (see Fig. 1). This paper concentrates on agent-based approaches for the study of wholesale and retail electricity markets.

A. Wholesale Electricity Markets

Agent-based Computational Economics (ACE) is the computational study of economic processes modeled as dynamic systems of interacting agents. ACE tools are used in [1] to study the dynamic efficiency and reliability of wholesale electricity market designs. The analysis uses two regional wholesale electricity market case studies for guidance: the New England Independent System Operator (ISO-NE) and the Midwest ISO (MISO). A computer-based framework is developed that models strategic traders interacting over time in a wholesale electricity market that is organized in accordance with core FERC market design principles and that operates over a realistically rendered transmission grid. Consultation is also occurring with ISO-NE and MISO industry stakeholders. The desired result is a field-tested open-source framework that rings true to energy industry participants, and that can be used by these participants and by academic researchers to conduct intensive sensitivity experiments.

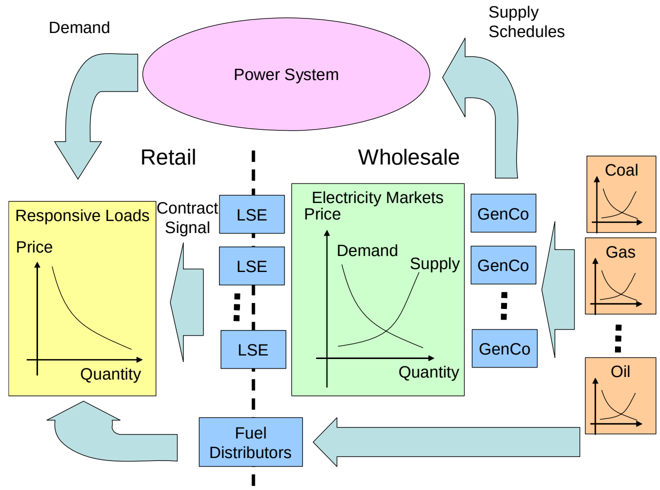

Fig. 1: An overview of input (fuel) markets and wholesale and retail electricity market interactions.

B. Retail Electricity Markets

Load Serving Entities (LSEs) forecast their aggregated resource needs and shop in the wholesale electricity markets available to them. To the extent that they offer price responsive incentive programs to their customers, they can use the demand elasticity inherent in these contracts to negotiate better deals from their wholesale suppliers.

Aggregation can be structured in various ways: 1) Demand response initiatives being advanced at the ISO level offer incentives for load relief across an entire region (LSEs in the region are expected to conform to the regional program). 2) Large commercial chains can reach agreements with electricity brokers for supply within a part of a region or across the country. 3) Distribution companies or independent load aggregators can combine manufacturing facilities, buildings, and residences in specific locations to amass elastic demand resources capable of playing in the wholesale markets.

What differentiates retail electricity markets from wholesale electricity markets? First, retail markets are more immature than wholesale markets, although knowledge and experience are growing. Next, given the increasing number of

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customers in retail markets, the per-customer transaction costs must be kept low. This means that a greater use of automated simple-to-configure systems is necessary. Lastly, once configured, preferences must be set up so that real-time decision making is also automated. This means that, in response to a change in real-time price or an emergency load reduction signal, the facility or premise needs to respond automatically. In essence, automated agents must act on behalf of customers to adjust their energy consumption consistent with pre-specified needs and desires.

Because of the nature of retail electricity markets, service providers structure their contract offerings differently than wholesalers. Households (residential consumers) might be offered a variety of programs meant to last a significant duration (a year or two) with options, incentives, and penalties to change based on the service providers' position and business forecasts. Although not designed for precisely the same marketplace, the wide variety of options provided by telecommunication service companies stimulates the imagination for electric services.

Even this picture simplifies the likely structure of the evolving electricity marketplace. Various types of intermediaries fulfill important roles and further complicate the overall organization of the market. The ability to model these intermediary roles will be important to simulations attempting to test electricity market designs, whether proposals or real-life developments.

II. Agent-Based Simulation Background

"A software agent is a computational entity that is capable of autonomous behavior in the sense of being aware of the options available to it when faced with a decision-making task related to its domain of interest." [2] In ACE market simulations, people, automated machine decision making, and other aspects of the physical world are represented by software agents. Two important features of ACE models are the agents' autonomous behavior in pursuit of some goal and their communal interaction, particularly their ability to communicate with each other.

An ACE model provides supporting infrastructure that allows agents to interact with one another in a simulated world, thus permitting researchers to study both individual and systemic behaviors. The architecture for an ACE model supports services such as:

- *Agent communication:* The communication between agents can follow a messaging pattern that respects the autonomy of each agent to act upon information. This information can be directed to specific agents or shared by many agents. Communication approaches involve the semantic aspects of messages (terms and their meaning, often documented in an ontology) as well as their syntax (format, from/to identification, etc.).
- *Configuration and execution management:* The various agents that make up a simulated world can be registered, organized, and tracked, in part through abilities provided to the simulator to start/pause/stop the simulation.
- *Activity logging:* The history of activity among agents can be stored. This includes consideration for the ability to "playback" events.
- *Model management:* Each agent in a simulated world can be initialized with a particular representation of the physical world aspect it is meant to simulate. These representations must typically be consistent across agents (e.g., the location of a generating unit is known to the generation company agent and to the ISO). Initialization, data storage, and data retrieval need to be appropriately supported across all agents.
- *Simulation time:* The speed at which an ACE simulation runs can be varied according to the nature of the simulation being performed. This may range from mimicking real-time to large step sizes that allow for simulations that span years. This involves coordinating a time clock across the simulated world and creating rules for agent development that allow agents to use this time to adjust their action steps.
- *Internal agent services:* Aspects of an agent in a simulated world can appear multiple times. For example, multiple agents might share the need for forecasting methods or learning tools. These can be offered as services configurable to the needs, desires, and behavioral dispositions of each agent.

A wide variety of existing tools and services are available to support ACE research [3]. Often tools are blended with custom software to create ACE frameworks to address specific issues of interest. The restructuring of electricity markets is one such issue. The next two sections present examples of ongoing ACE research focusing on the restructuring of wholesale and retail electricity markets.

III. Wholesale Electricity Market Testing

The ACE wholesale electricity market framework developed in [1] - referred to as AMES (Agent-based Modeling of Electricity Systems) - is programmed in Java using RepastJ, a toolkit designed specifically for agent-based modeling in the social sciences [4]. The framework is being designed to be modular, extensible, and open source in order to provide a useful foundation for further electricity research. In particular, the goal of the larger NSF project [5] encompassing the development of the AMES framework is to explore ways of achieving a more effectively integrated U.S. bulk energy transportation network comprising electricity, natural gas, coal, and water subsectors.

The AMES framework incorporates in stylized form several core elements of FERC's proposed Wholesale Power Market Platform (WPMP), a market design implemented for New England by the ISO-NE and for the Midwest by the MISO. By adhering closely to the architecture of these regional markets, advantage is being taken of the voluminous training guides and operational manuals publicly released by the ISO-NE and the MISO.

The core elements of the WPMP currently incorporated into the AMES framework are as follows (see Figures 2 and 3):

1. The AMES wholesale electricity market operates over a possibly non-radial AC transmission grid.
2. The AMES wholesale electricity market includes an independent system operator (ISO) and a collection of load-serving entities (LSEs) and generators distributed across the nodes (buses) of the grid.
3. The AMES ISO undertakes the daily management of a day-ahead market and a real-time market, as well as a supply re-offer period for generators.
4. The AMES ISO determines power commitments and locational marginal prices (LMPs) for the day-ahead market based on generator supply offers and LSE demand bids (forward financial contracting). Any differences that arise between the contracts cleared in the day-ahead market and real-time conditions are settled by the AMES ISO in the real-time market at real-time LMPs.
5. Transmission grid congestion is managed via the inclusion of congestion components in LMPs.
6. AMES energy traders have access to a (point-to-point) financial transmissions rights (FTR) market as a hedge against congestion-induced price volatility in the day-ahead market.

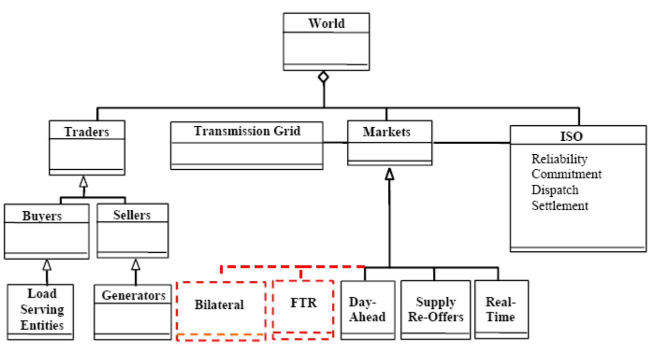

Fig. 2: AMES architecture (agent hierarchy)

Additional aspects (e.g., bilateral trading) will be incorporated at a later time to more fully reflect the dynamic operational capabilities of the WPMP.

The AMES energy traders are cognitive entities with private data and with various public and private methods enabling them to operate autonomously in their market environment. In particular, the traders learn over time how to make their demand bids and supply offers on the basis of past experience in an attempt to increase their profits.

Currently the AMES energy traders determine their market actions by some form of reinforcement learning, such as the stochastic reinforcement learning algorithm developed in [6] on the basis of human-subject experiments. This reinforcement learning is implemented for each trader by a reinforcement learning module that permits a variety of different reinforcement learning representations. In later extensions of AMES, other forms of learning (e.g., social mimicry and anticipatory learning) will also be considered.

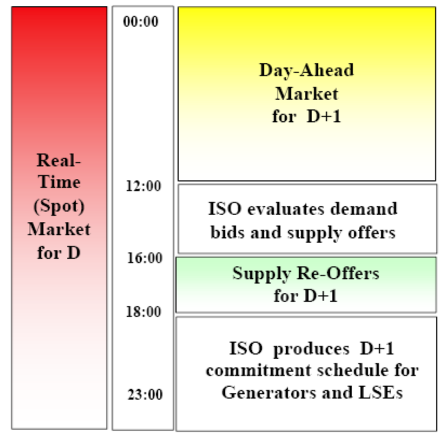

Fig. 3: AMES ISO daily activities for day D

As in the ISO-NE and the MISO, the AMES ISO determines power commitments and LMPs for each hour of the day-ahead market by means of a DC power flow. The solution maximizes total net benefits subject to constraints reflecting both physical considerations (e.g., loop flow effects) and the need for balancing demand and supply at each transmission grid node. The AMES ISO also repeatedly solves related DC power flow problems for each hour of the real-time market to settle any differences that arise between day-ahead plans and the real-time state of the wholesale power market.

These various components of the AMES framework are currently being integrated into a dynamic wholesale electricity market model that will be used to conduct intensive experimental testing of the operation of the market over time. The following list outlines several planned experiments.

1. In parallel with the ISO-NE and the MISO, the AMES ISO generates LMP and power solutions using DC power flow approximations for actual underlying AC power flow problems considered too costly to solve in normal run-time operation. What types of errors are generated by these approximations?
2. How well does the WPMP market design perform when the AMES generators use alternative learning methods to determine their supply offers for the day-ahead market?
3. How well does the WPMP market design perform under alternative assumptions regarding AMES LSE demands (fixed loads versus price-sensitive demand curves versus active demand-side bidding with learning)?
4. How well does the WPMP market design perform under different AMES market concentration conditions (i.e., different numbers and sizes of generators and LSEs)?
5. To what degree does the WPMP two-settlement process in the AMES framework (the combined working of the AMES day-ahead and real-time markets) help AMES traders hedge against the risk of excessive price volatility?

6. To what extent does the WPMP-recommended inclusion of an FTR market help AMES market participants hedge against the risk of congestion-induced costs in the AMES day-ahead market?
7. Bilateral trades arranged up to many months in advance could play a critical role in helping traders to manage market risk. How does an opportunity to engage in bilateral trades affect AMES market performance?
8. To what extent do the core WPMP features incorporated into the AMES framework provide appropriate incentives for investment in new generation and new transmission facilities?

For many of these design issues, the impact of price-sensitive demand and other distributed energy resources on LSE behavior and WPMP performance could be significant. To adequately pursue these issues, load models that adequately reflect the potential influence from retail markets will therefore need to be incorporated into the AMES framework.

IV. Retail Electricity market Testing

The future energy system will apply the expansive capabilities of information technology to coordinate distributed energy resources (DER - including demand, distributed generation, and storage) with bulk transmission and generation resources to enhance system performance and reduce the impact of component failure (both technically and economically). To accomplish this transformation, the traditional paradigm of meeting all demand at a fixed cost at all times is giving way to more interactive, transparent mechanisms that recognize the value of an array of energy services to those participants with a need. This entails the establishment of markets for the exchange of services, and a mechanism to obtain information to support good decision making. The term GridWise™ reflects a vision for this transformation [7].

Classical load models look at the probabilistic behavior of load averaged over different times of day and various times of the year. These models also reflect aggregated contributions from many different types of appliances and equipment used in industry, commercial buildings and homes. However, to study the impact of demand response programs and distributed generation usage, detailed equipment and human behavior modeling must be included in the simulation.

Such detailed demand-side modeling has been done for residential neighborhoods [8], [9]. Fig. 4 shows the pulsed nature of appliance load on the distribution system over the course of a day. The number of households must increase significantly before we begin to see the diversity usually represented in traditional load models. To simulate the interaction with market signals, the load models need to include price-responsive controllers. Such controllers might adjust thermostat set-points or directly curtail energy delivery to an appliance, thus altering the nature of these pulses. In addition, human behavior patterns might change to move load to shoulder or off-peak periods if given the right financial incentive. A number of building and home automation products are entering the marketplace. With simple signals from LSEs, facilities can be preprogrammed to respond to prices or emergencies in a prioritized manner that reflects household preferences [10].

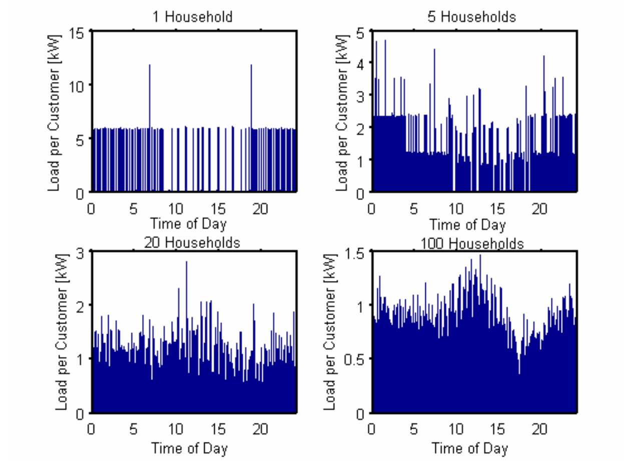

Fig. 4: Load diversity as household loads increase

Given the thousands of buildings and appliances that can be fed from a distribution feeder, configuration tools must be provided that allow simulated retail electricity markets to be populated relatively easily while still preserving realistically diverse behaviors. Given broad regional characteristics, individual buildings each with their own appliances and human behaviors must be modeled if the complex behavior that emerges from the interaction of such a large number of devices is to be revealed. Statistical mechanisms are used to help populate the individual building models from aggregated parameters measured in neighborhood areas.

The economic simulation aspects are handled using ACE modeling tools similar to those used for the wholesale electricity market study discussed in Section III. Thus, customers, LSEs, and distribution system operators are all modeled as software agents (Figure 5).

Though a variety of different auction forms (call, blind, English, Dutch, etc.) might be appropriate at the wholesale market level, only a few options are reasonable for the LSE to offer to customers in a retail environment. Besides the fixed price contracts that most customers face today, some retail offerings also include time-of-use (TOU) rates or real-time pricing (RTP) signals.

The behavioral element critical in any modeling of market behavior is the mechanism by which the actors formulate demand bids or supply offers. We have explored genetic algorithms (GAs) as well as an approach to customer behavior more defensible in terms of human psychology – the modified Roth-Erev method (MRE) [11]. The application of the MRE method to the retail level relies on a fitness measure that, for households, depends on household type, the history of utility expenditures relative to income, and the level of service implied by different characteristics of the household.

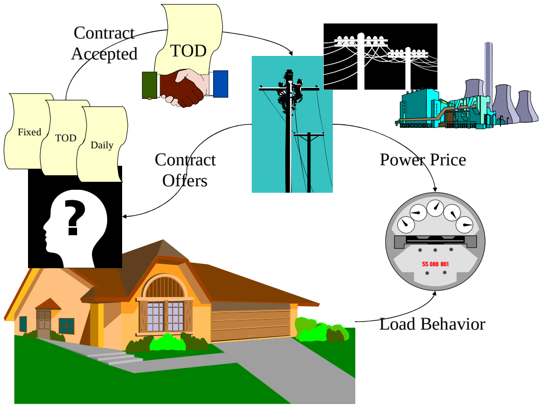

Fig. 5: Customer, LSE, and distribution company economic interactions

At the core of the strategy for constructing a price-responsive retail electricity market consisting of households and a distribution utility is the decision to adopt a specific type of contract that has advantages both for households and for the utility. The advantages for the utility come from sharing the risk of wholesale price fluctuations that affect the utility's costs; the advantages for the households come from being able to manage better their utility bills and, with that better management, to reduce their utility costs.

A major challenge is the development of a "fitness measure" that triggers a switch from one sort of contract to another. The agents that accept new contracts have to migrate from the current pattern of use under the old contract to the new pattern of use under the new contract encouraged and aided by incentives in the form of technology to manage loads and lower power bills.

Simulated households review their bills and determine if a contract change is in order. Incentives are also modeled for LSEs to offer alternative contracts. LSEs will set and adjust the terms of their contract offerings as they learn to better predict (forecast) household response. The idea is to play out the resulting dynamic to gain insight into the viability and stability of various contract offerings.

Simulation time scales might also vary widely depending upon what aspect of a retail electricity market is being studied. For example, to gain insight into the behavior of appliance controllers and households responding to emergency signals, a simulator would need resolution at short time frames so that the dynamics of a diverse set of resources could be reviewed. At the other end of the time spectrum, a simulator might be more interested in contract choice and the market dynamics of introducing contract changes or new offerings to households. To smooth out seasonal affects from periods of the year in which prices regularly spike or dip, the simulator might then need to review simulated multi-year histories to investigate long-term household trends to accept or abandon particular contract offerings. ACE frameworks permit simulators to include time frames flexibly tailored to the study at hand, so that relevant results can be obtained within a reasonable number of computational periods.

The insights gained at the retail and distribution levels of an electricity market can help formulate simplified models to aggregate response for wholesale market tests. Regional dependencies on climate and personal behavior in addition to the nature of retail power contracts affect how these reduced-order models are constructed. An approach to creating such a simplified model for heating, ventilation, and air-conditioning (HVAC) systems is reported in [12]. Important to the realization of these reduced-form models is the ability to capture the complex behavior that emerges from large populations of appliances under price signals. For example, a high real-time price signal might result in a relatively quick reduction of load on a feeder; however, it could also reduce the diversity of the load so that, after prices fall or consumer discomfort sets in, the rebound need for electricity exceeds the original peak.

V. The Agent Pattern in Actual Operations

A great advantage of ACE frameworks is their potential facilitation of real-time operations. Business process automation continues to advance to the point where heterogeneous systems of autonomous agents are mixing with human interactions to deliver new capabilities and enhance productivity. ACE frameworks permit the study of learning agents engaging in realistic operational interactions. Consequently, the learning algorithms embedded in these agents could become applicable for decision makers in actual operational environments.

Standards for operational environments, such as those being developed by the Foundation for Intelligent Physical Agents FIPA [2], as well as advances in electronic commerce approaches such as service-oriented architectures, are facilitating the interaction of agents across software platforms. This is enabling the modeling of large complex systems of systems. These developments are transforming the operation of electricity markets as well as banking, telecommunications, entertainment, shopping, and shipping.

Besides enabling the testing of market designs and potential participant interactions, the logic used in ACE frameworks to construct agents representing generators, LSEs, ISOs, and other electricity market participants might provide valuable guidance for how real-world market participants could automate their decision-making and learning tools to increase their effectiveness in the market. Tools found useful for evaluating market behavior and for discovering and attenuating market power in ACE electricity market simulations might also find applicability as real-time market monitoring tools in operational electricity markets.

Intelligent systems are now being deployed in industrial, commercial, and residential settings. Within each setting, agent-based software is being developed to represent appliances and other energy consuming equipment in a distributed form of energy management. The agent-based learning and decision-making algorithms being tested in the analysis environment directly apply to agents that might live in a piece of process equipment or your home clothes dryer.

At the facility management level, consumer "portals" are being demonstrated for interfacing with metering equipment, LSEs and distribution system operators. Many aspects of the agent logic used to mimic consumer preferences and the dynamics of LSE contract offerings can be considered as potential starting places for automation in actual operational settings.

The US Department of Energy has established the GridWise Architecture Council [13] to articulate the guiding principles that constitute the architecture of a future, intelligent, transactive energy system. The Architecture Council comprises practitioners and leaders with broad-based knowledge and expertise in power, information technology, telecommunications, financial systems, and additional relevant sectors working together toward a coordinated GridWise vision—the transformation of the nation's energy system into a rich, collaborative network filled with decision-making information exchange and market-based opportunities.

This group and others (such as organizations that participate in FIPA) are looking to identify the key points to establish agreement where automation between independent parties can enable a new frontier for delivering services and motivating investments in electric power. The knowledge gained from agent-based simulation environments will have direct applicability to how this new world develops.

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VII. Biographies

Steve Widergren (M'1978, SM'1992) received his BSEE (1975) and MSEE (1978) from the University of California, Berkeley. He works at the Pacific Northwest National Laboratory, where he contributes to the research and development of new solutions for the economic and reliable operation of power systems. Prior to joining PNNL, he was with ESCA Corp. (now Areva T&D), a bulk transmission energy management system supplier, where he designed software solutions for system operations and championed the establishment of an integrated suite of energy management system software products. He has also held power engineering positions at American Electric Power and interned at Pacific Gas & Electric. He is Vice-Chair of the Richland Section of IEEE, active in the Power Engineering Society, and has participated in IEEE and IEC standards efforts that bridge power engineering with information technology.

Junjie Sun is a Ph.D. candidate in economics at Iowa State University specializing in financial economics, macroeconomics, and statistics. His current research interests include applying the agent-based computational method in economic analyses of energy markets and financial markets, and non-parametric and semi-parametric estimation of macroeconomic and financial data.

Leigh Tesfatsion (M'2005) received her Ph.D. in economics, with a minor in mathematics, from the University of Minnesota in 1975. She is currently professor of economics at Iowa State University, with a courtesy appointment as professor of mathematics. Her recent research has focused on Agent-based Computational Economics (ACE), the computational study of economic processes modeled as dynamic systems of interacting agents. With Junjie Sun, she is developing an ACE framework to explore structure, behavior, and market power in restructured wholesale power markets. She serves as associate editor for the *Journal of Economic Dynamics and Control*, the *Journal of Public Economic Theory*, the *Journal of Economic Interaction and Coordination*, and *Applied Mathematics and Computation*, and is a past associate editor for the *IEEE Transactions on Evolutionary Computation* (1996-2002). She is an active participant in the Society for Computational Economics (SCE), serving twice as an elected member of the SCE Advisory Council. She is also active in the IEEE PES Task Force on Multi-Agent Systems.