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Using Agent-Based Computational Economics To Understand The Evolution Of The Electric Grid In Response To Increased Penetration Of Distributed Solar Generation

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Abstract: This report summarizes recent research using agent-based computational economic modeling (ACE) in the electricity industry and illustrates how ACE can be used to investigate the dynamic response of a traditional electric grid in response to increased penetration of distributed solar generation. Using a hypothetical electric grid, the ACE model describes the dynamic behavior of four different economic agents. Submodules account for the wholesale electricity market and the decision to invest in a rooftop solar system by end-use electricity customers. These submodules are coupled in that retail electricity prices determine the costs associated with forgoing an investment in distributed solar generation while the decision to invest in distributed solar generation determines the load demand in the wholesale electricity market. While the results presented in this report are illustrative and not prescriptive, they do highlight a number of interesting trends. First, increased penetration of DG will have large impacts on dispatch at traditional generating units and locational marginal prices on the grid. The 55-66 percent reduction in retail customers we observe in our simulations will likely exacerbate recent coal plant retirements. Second, decreased load demand due to adoption of DG technologies will have a large impact on high-cost generating units in the system but may have little impact on nuclear plants that generate electricity at a relatively low cost. Third, transmission line constraints matter. Transmission line constraints imply that the marginal cost of serving customers will vary across the utility's service area. This suggests that certain generating units and demand in certain LPCs will have a disproportional influence on the impacts of DG and the utility's ability to respond to increased penetration of PV systems.

1. INTRODUCTION

As small-scale electricity generation technologies become more cost-effective, many firms, governments, and even private individuals have expressed interest in on-site electricity generation to address environmental and fuel security concerns. In 2015, the United States had over 15,500 MW of distributed and dispersed generation capacity, which is about 1.5% of the capacity of the nation's centralized power plants (EIA 2015). DG in the buildings sector is expected to increase from around 5 GW in 2013 to about 30 GW by 2040 (EIA 2013). The increasing adoption of these small-scale technologies represents a transition from a hub-and-spoke system of centralized electricity generation to distributed generation (DG).[1] DG, the use of small-scale technologies to generate power close to end users, provides many opportunities and challenges for electric utilities. For example, DG can allow utilities to defer generation capital investments, avoid energy costs, achieve environmental compliance, sell valuable renewable energy credits (RECs), and lower transmission and distribution system energy losses. Challenges include intermittent generation, stranded assets, inability to dispatch, and an inability to control when generation is produced ("must take" energy). Many utilities understand the benefits of DG but are unsure of how to mitigate these challenges.

To date, much of the academic research on DG has focused on three areas. The first is engineering research that investigates the impact of DG within portions of the physical system (e.g., Bouzid et al. 2015). The second is economic research on the adoption of DG technologies such as photovoltaic (PV) systems (i.e., rooftop solar). Observed investment behavior in PV technologies suggests that customers discount the future benefits of these investments (electricity savings and potential revenues from resale of excess electricity) at an excessively high rate of 7-21% when evaluated using standard discounted cash flow approaches (Rai and Sigrin 2013). This implies that in many cases households choose to forgo cost-effective investments in DG. Potential explanations for this seeming under-investment include social interaction or peer effects (Bollinger and Gillingham 2012), hidden costs (Burkhardt et al. 2015), and uncertainty concerning key determinants of the investment such as unexpected changes in electricity rate structures and solar incentive programs (Torani et al. 2016).

The third are studies that investigate the diffusion of solar technologies and the impacts of this diffusion on the electric grid. These studies seek to partially integrate the engineering and economic research to investigate the complex dynamic feedback relationships between the physical architecture of the grid (e.g., location of generation capacity, transmission network), financial and public relation incentives of grid managers (e.g., cost and outage minimization), and investment decisions made by utility customers (e.g., investment rules utilized, risk-return tradeoffs, availability of information). Current frameworks used to investigate DG's impact on the electric grid can be categorized as either top-down or bottom-up. Top-down approaches include systems modeling frameworks that focus on how dynamic interdependencies between different systems such as the electric grid and electricity markets influence the rate and extent of solar technology diffusion and electric grid performance at an aggregate level. Examples include the Regional Energy Deployment System (ReEDS), developed by NREL; Solar Deployment System (SolarDS) model, developed by NREL; and the Financial Impacts of Distributed Energy Resources (FINDER) model, developed by Lawrence Berkeley National Lab.

An important limitation of these top-down approaches to investigating the effect of PV integration on the grid is that the behavior of the aggregate system is simply the sum of the individual systems. Bottom-up approaches allow for emergent system behavior that would not be predicted

[1] The Institute of Electrical and Electronics Engineers (IEEE) defines distributed generation as the generation of electricity by facilities that are sufficiently smaller than central generating plants so as to allow interconnection at nearly any point in a power system (Dondi, Bayoumi et al. 2002). For customers, DG is a potential alternative to or enhancement of the traditional electric power system and can encompass many different technologies including combined heat and power (CHP), photovoltaic (PV) systems, small wind turbines, and hybrid systems. For electricity suppliers, DG can help provide clean power and reduce system losses along transmission and distribution lines.

from an analysis of the systems at an aggregate level – the aggregate behavior is not simply the sum of the individual parts. This emergent behavior becomes particularly important for describing the impact of DG since the emergence of DG implies an electric grid with many new players, new rules, and new behaviors.

This paper utilizes an agent-based computational economics (ACE) approach to illustrate how the location of PV systems on the grid determines whether the challenges that arise from PV exceed the potential benefits for an electric utility.[2] ACE is a bottom up approach to modeling the electric grid where the behavior of agents (customers, generation plant operators, utility managers) within the electrical system is modeled with explicit consideration given to the social, economic, and physical relationships between these agents. The model is used to undertake a simulation experiment that compare electric system performance with and without policy incentives intended to lower the cost of PV systems and encourage their adoption. Electric system performance is evaluated based on both economic metrics (revenues, customer welfare, and locational marginal prices) and engineering metrics (unit dispatch, load constraints). The spatial and temporal dynamics in our model also allow use to investigate the distribution of the economic and engineering metrics across the grid (separation) and over time (volatility).

Our modeling activities build off of the existing Agent-based Modeling of Electricity Systems (AMES) (Sun and Tesfatsion 2007). AMES models strategic traders interacting over time in a wholesale power market that is organized in accordance with core wholesale power market features and that operates over a realistically rendered transmission grid. For this study, the AMES modeling platform was amended in two ways. First, we allow for customer electricity demand to be sensitive to electricity rates. One potential concern among utilities is the utility death spiral (Laws et al. 2017). As customers adopt DG, utilities are forced to raise rates to cover the large fixed capital costs associated with generation and transmission. Rate increases then increase the electricity costs associated with traditional electricity triggering more DG adoption. Customer demand in AMES is insensitive to electricity rates which exacerbates the utility death spiral. In our study, customer demand for electricity is based on electricity sales data from the six largest utilities in the service area. Second, we create a new end-use customer agent type that allows us to investigate DG investment behavior. Unlike AMES where customer demand is aggregated to the local utility level, our model disaggregates local utility demand to different individual customer types which will allow us to investigate how differences in socio-economics and information influence decisions to invest in DG and how these micro-level investment decisions influence macro-level outcomes such as dispatch and pricing.

The paper begins with a brief overview of distributed generation in the United States. The subsequent section details agent-based computational economics, highlights applications to the electric industry and describes the AMES wholesale power market testbed. The third section reports on the findings of the study. This section includes a detailed description of the agent-based model of DG adoption along with the data statistical methods used to parameterize the model. Results include

[2] Photovoltaic (PV) systems account for more than 90% of installed DG in the U.S. and have shown significant growth over the past few years (EIA 2015). Between 1998 and 2014, PV capacity increased over 50% per year (Barbose et al. 2015). Between 2014 and 2015, total estimated distributed PV generation increased 27% (12,141 GWH). Most of this growth has occurred in the residential (49%) and commercial (41%) sectors.

a "benchmark" simulation of DG adoption based on publically available information on utility demand, generation assets, and expected rates of DG innovation. Section 5 reports on results of two simulation experiments where benchmark simulation results are compared to two counterfactual simulations. The first assumes all customers participate in a state/utility solar incentive program that lowers the cost per watt of solar-generated electricity. Comparing this counterfactual to the benchmark indicates how solar incentive programs altered the timing and location of solar adoption in the service area. The second counterfactual considers DG adoption in the presence of recent retirement of coal-fired generation. Comparing simulation results from this counterfactual to the benchmark simulation indicates how two current transitions in the electric industry (coal to natural gas and centralized to distributed generation) have amplified or mitigated one another. The paper closes with a brief discussion and concluding remarks.

2. AGENT-BASED COMPUTATIONAL ECONOMICS

2. 1. Overview

Models of complex systems such as the human-engineered electric grid can be broken down into two categories: top-down (systems) models and bottom-up models. Top-down models combine detailed models of the physical system with aggregate characterizations of human behavior. Aggregate characterizations typically employ models that describe equilibrium market behavior with a representative agent or game theory. Equilibrium models either do not consider strategic bidding behavior or assume that players have all relevant information about the other players' characteristics and behavior. Equilibrium models also disregard the consequences of learning effects from daily repeated interaction. Game theoretical analysis is usually limited to stylized trading situations among few actors, and places rigid assumptions on player behavior.

Agent-based modeling (ABM) is a bottom up approach that researches the two-way feedback between regularities on the macro level and interaction of economic actors on the micro level. In Artificial Intelligence (AI) terms, an agent is an autonomous program acting independently but on behalf of another agent or possibly a human user (Vlassis 2003). Agents typically have some set of rules or behavior patterns that effect a change on the agent itself and its outside environment including other agents (North and Macal 2007). Agents typically do not work in isolation, but combine to form multi-agent systems (MAS) that interconnect separately developed agents and thus enable the ensemble to function beyond the abilities of any singular agent in the system (Vlassis 2003; Vidal 2007). Agents can coordinate, collaborate, negotiate and learn to ensure interdependencies between agents and MASs are properly managed. Researchers in fields of organizational theory, economics, and anthropology have studied the topic of agent coordination through (1) organizational structure networks; (2) contract net protocols (CNP); and (3) multi-agent planning (Anumba *et al* 2005). Negotiation is a main method for coordination that enables a group of agents to arrive at a mutual agreement regarding beliefs, goals, or plans through (1) contract-based negotiation; (2) plan-based negotiation; (3) market-based negotiation; (4) game-theory based negotiation; (5) AI-based negotiation such as case reasoning and k-b approaches, and (5) psychology-based negotiation (Ren *et al* 2003). When working with MAS, it is hard to predict or foresee all of the potential situations an agent might encounter in such open, complex, and dynamic environments.

Accordingly, there has been considerable research in the area of MAS learning including (1) reactive-reinforcement learning whether deterministic or stochastic; (2) belief-based learning; (3) anticipatory learning such as Q-learning; (4) evolutionary learning such as genetic algorithms; and (5) connectionist learning such as neural networks (Anumba *et al* 2005).

Agent-based computational economics (ACE) is a special case of ABM that focuses on computationally modeling economic processes as open-ended dynamic systems of interacting agents. ACE provides many advantages over top-down systems models for modeling electricity markets. First, it avoids the need to make assumptions about emergent system behavior which could potentially generate misleading results. For example, aggregate metrics such as utility profits, customer satisfaction, and electricity rates are determined solely by individual agents interacting with one another on the electric grid. Second, it allows for heterogeneity among agents, imperfect information, and the dynamic responses of individual agents. Agent-based modelers are not restricted to equally sized or symmetric firms, representative agents, prefect information, or a single stable equilibrium. Instead, every agent making up the modeled economy can be designed independently. The economy then evolves as a result of the interplay of these heterogeneous agents, i.e. from the bottom-up. These considerations have been shown to influence system performance and efficiency in Wholesale Power Market Platforms in New England and the Midwest.

The ACE modeling procedure can be described as follows (Tesfatsion 2002). After having defined the research questions to resolve, the modeler constructs an economy including an initial population of agents and subsequently specifies the initial state of the economy by defining the agents' attributes (e.g. type characteristics, learning behavior, knowledge about itself and other agents) and the structural and institutional framework of the market within which the agents operate. The modeler then lets the economy evolve over time without further intervention. All events that subsequently occur must arise from the historical time-line of agent-to-agent interactions. Finally, simulation results are analyzed and economic theory is used to evaluate of the regularities observed in the simulated data. Because no assumptions about the macroeconomic outcomes are necessary, seemingly irrational agents may yield macroeconomic behavior that largely conforms to the rational, representative agent paradigm. Conversely, a population of largely rational agents may yield macroeconomic behavior that appears irrational compared to traditional economic models.

2. 2. Applications to the electricity industry

The electricity sector is characterized by difficult real-world aspects such as complex networks, asymmetric information, imperfect competition, strategic interaction, collective learning, and the possibility of multiple equilibria (Tesfatsion 2006). While these real-world aspects strain traditional economic modeling techniques, agent-based computational economic models are an ideal tool for studying electricity market performance. Not surprisingly, there are a growing number of agent-based modeling applications to the electricity industry. These applications can be broken down into three categories.

The first category uses agent-based models to examine consumer behavior at the retail level. Hämäläinen et al. (2000) use an agent-based approach to study the consumption strategies of individual electricity buyers in a coalition. Roop and Fethelrahman (2003) use an agent-based model of the distribution system to model changes in residential contracts at the retail level. The results show that the system is more responsive to peak prices with these contract changes. Yu et al. (2004) design an agent-based retail electricity market to simulate trading behavior between power exchanger agents, retail customers, local utilities, and independent power plant operators. The simulation results illustrate how the retail market could be adjusted to improve efficiency, reduce operational cost, and increase alternatives for consumers. Müller et al. (2008) develop an agent-based simulation model to investigate the interdependencies between the customer's engagement in the German retail market and the supplier's pricing strategies. Based on a series of simulations, the authors conclude that greater customer participation in the German retail market will be unable to stop observed increases in real prices.

The second category provides agent-based decision support tools for power market participants. Praça et al. (2004) develop a multi-agent model of competitive electricity markets that is designed as a decision support tool for market stakeholders. The model allows for different types of markets (e.g., bilateral contracts, pool mechanisms) and strategic behavior by buyer agents but is limited in its specification of the electric grid and the behavior of generation companies. Bernal-Agustín et al. (2007) present a realistic simulator of the day-ahead electricity market for mainland Spain. Harp et al. (2000) develop an agent-based simulator designed for use by electric power industry agents to ease the transition from regulated to deregulated electricity markets. Several U.S. and Australian laboratories are currently developing large-scale models designed as a decision support for concrete policy making in deregulated electricity markets.

- Electricity Market Complex Adaptive System (EMCAS) developed by Argonne National Laboratory (Conzelmann et al. 2005)
- Marketecture from Los Alamos National Laboratory (Atkins et al. 2004)
- Agent-Based Laboratory for Economics (N-ABLE) developed at Sandia National Laboratory (Ehlen and Scholand 2005)
- Simulations for Coupled Systems within the GridWise program at Pacific Northwest National Laboratory (Widergren et al. 2004)
- Australian National Electricity Market Simulator (NEMSIM) developed at CSIRO (Batten and Grozev 2006)

The third category concentrates on the analysis of market structures and market design for the wholesale power market. Bower and Bunn (2001) show that simulated market clearing prices are lowest in the case of daily bidding with uniform pricing, and highest in the case of hourly bidding with discriminatory pay-as-bid settlement. Bunn and Oliveira (2007) investigate whether strategic generator agents in electricity markets evolve into diversified players with a mix of base load, shoulder and peak load plants, or into specialized players that seek to dominate the market in their segment. In a series of papers, Visudhiphan and Ilić (1999; 2001; 2002) compare different adaptation learning algorithms applied to generator agents. Rupérez Micola et al. (2006) use an agent-based model to study vertical integration in the energy sector. Several studies have investigated different forms of agent learning in an agent-based model including genetic algorithms (Richter and Sheblé 1998; Nicolaisen at al. 2000; Lane et al. 2000), Roth Erev learning (Nicolaisen et al. 2001; Petrov and Sheblé 2001; Weidlich and Veit 2006), and Q-learning (Krause and Andersson 2006).

2. 3. AMES wholesale power market test bed

In 2003, the U.S. Federal Energy Regulatory Commission (FERC) proposed the core design feature of the wholesale power market. Though FERC's model has been implemented by various U.S. Energy Regions[3], strong criticism of the design persists. A computational laboratory for Agent-based Modeling of Electric Systems (AMES) was developed to provide systematic experimental study of wholesale power markets restructured in accordance with FERC's market design (Sun and Tefatsion 2007; Li et al. 2009).

The JAVA based AMES laboratory operates over a user-specified AC transmission grid, and it includes an Independent System Operator (ISO) and a collection of energy traders consisting of Load-Serving Entities (LPCs) and Generation Companies (GenCos) distributed across the buses of the transmission grid. GenCos use stochastic reinforcement learning to adaptively choose its supply offers based on the net earnings outcomes of past actions. GenCos and LPCs are distributed across buses of the transmission grid and each of these entities is implemented as a software program encapsulating both methods and data. The independent system operator (ISO) uses LPC fixed demands (loads) and GenCo supply offers as input data for DC optimal power flow (OPF) problems. The solution to the OPF problems is a series of hourly dispatch and electricity prices for the day-ahead market that minimizes the cost of meeting a given load profile.

AMES operates on a daily time step and each day *D* consists of 24 successive hours *H* = 00, 01, …, 23 to capture electricity demand variation during the day. The ISO is charged with the operation of a day-ahead market settled by locational marginal prices (LMP). Locational marginal pricing is a way for wholesale electric energy prices to reflect the value of electric energy at different locations, accounting for the patterns of load, generation, and the physical limits of the transmission system. Unlike fixed rate structures, LMPs account for both the location and timing of its injection into or withdrawal from the transmission grid. Each LPC seeks to secure the highest possible net earnings each day by purchasing power in the day-ahead wholesale power market and reselling this power to its downstream (retail customers). During the morning of each day *D*, each LPC reports a user-specified demand bid to the ISO for the day-ahead market *D*+1. Each demand bid consists of a fixed demand bid in the form of a 24-hour load profile.

Also during the morning of each day *D*, each GenCo uses its current action choice probabilities to choose a supply to report to the ISO for use in all 24 hours of the day-ahead market for day *D*+1. Each supply offer consists of a linear marginal cost function defined over an operating capacity interval. Each GenCo seeks to secure for itself the highest possible net earnings each day through the sale of power in the day-ahead market. GenCos can experiment with its choice of supply offer by varying the slope and/or intercept of its reported supply offer and/or the upper limit of its reported operating capacity in an effort to increase its daily net earnings.

[3] Versions of FERC's wholesale power market design have been implemented in the Midwest (MISO), New England (ISO-NE), New York (NYISO), the mid-Atlantic states (PJMB), California (CAISO), the southwest (SPP), and Texas (ERCOT).

The objective of the ISO is the maximization of electricity generator and consumer net surplus subject to generation and transmission constraints. At the end of each day *D*, the ISO settles all of the LPC and GenCo payment obligations for the day-ahead market for day *D*+1 based on the LMPs for the day-ahead market for day *D*+1. The settled (cleared) market is characterized by hourly dispatch for each GenCo and LMPs for the day-ahead market for day *D*+1 based on the demand bids from LPCs and reported supply offers from each GenCo. Hourly dispatch and LMPs are the solution to hourly bid/offer-based DC optimal power flow (DC-OPF) problems. OPF is a classic optimization problem where the objective is to minimize the cost of electricity generation subject to equality constraints that balance power at each node in the transmission network and inequality constraints that reflect network operating limits (line flows, voltage limits) and limits on management actions. Based on its day *D* settlement payment, each GenCo uses a variant of a stochastic reinforcement learning algorithm (Roth and Erev 1995; Erev and Roth 1998) to update the action choice probabilities currently assigned to the supply offers in its action domain. Specifically, if the supply offer reported by GenCo on day *D* results in a relatively good reward, the GenCo increases the probability of choosing this supply offer on *D*+1. Conversely, if the supply offer results in a poor reward, the GenCo decreases the probability of choosing this supply offer on day *D*+1.

There is no entry of traders into or exit of traders from the wholesale power market. Each LPC and GenCo has an initial holding of money that changes over time as it accumulates earnings and losses. LPCs and GenCos are allowed to go into debt without penalty or forced exit. The model also assumes no system disturbances or shocks that would void the financial contracts determined on each day *D* for the day-ahead market for day *D*+1. This implies that a real-time market for electricity is unnecessary.

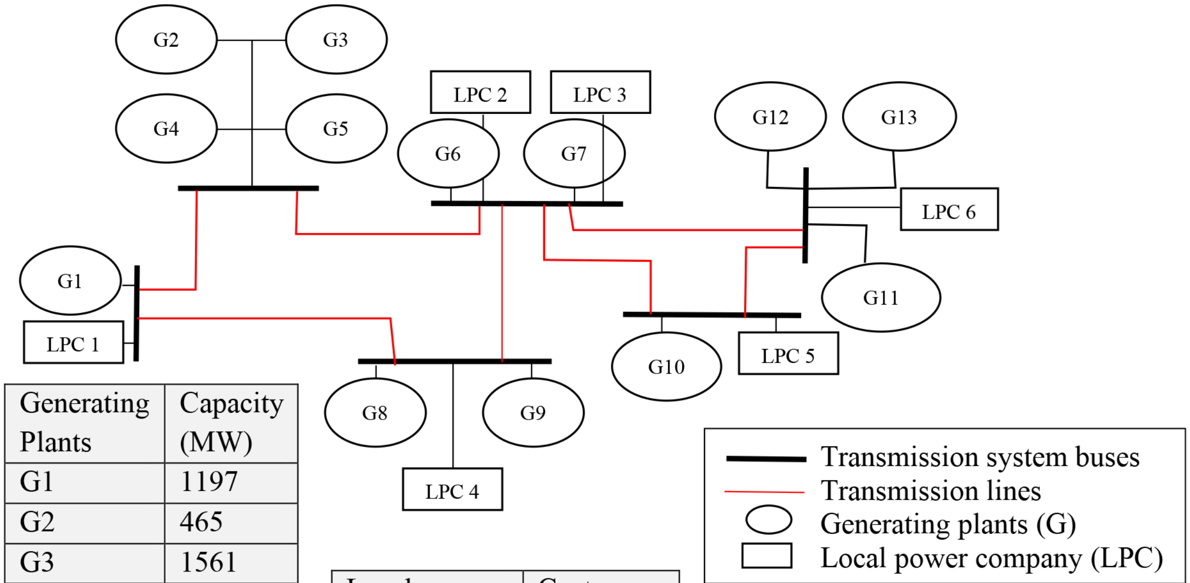
AMES has been used to investigate the efficiency of deregulated wholesale power markets in response to transmission network configurations, new technology, customer behavior, GenCO learning, and market operations. Sun and Tesfatsion (2007) find that GenCos quickly learn to tacitly collude on supply offers resulting in LMPs substantially higher than competitive price levels. Li et al. (2008) investigate the use of price caps to combat the market power exerted as a result of GenCo learning. They find that the imposition of a binding supply offer price cap by the ISO results in lower LMPs on average but also increases average LMP spiking and volatility. Li et al. (2009) investigate the effect of more experimental and adaptive GenCos, demand-bid price sensitivities, and supply offer price caps on separation and volatility of LMPs. Li et al. (2011) test various institutional arrangements in electricity markets while Li and Tesfatsion (2012) investigate global market patterns that arise and persist over time as a result of seller co-learning. Krishnamurthy, Li, and Tesfatsion (2016) undertake a careful application of AMES to the ISO-New England market.

3. ACE APPROACH TO INTEGRATING DISTRIBUTED SOLAR ON THE GRID

Our modeling and simulation experiments are based on a hypothetical electric grid (see Figure 1) that includes six local power companies (LPC) and thirteen generating plants distributed between six transmission system buses. Each bus in the grid supports at least one generating plant or LPC. LPCs purchase electricity and are characterized by a price-sensitive demand function that determines how much an LPC is willing to pay for a given amount of power. Electricity generation is characterized by fixed and variable costs of generation and technical constraints on plant operation (e.g., minimum operating time). Each transmission bus is connected to at least one other bus through a transmission line. The distance of a transmission line coupled with the thermal and capacity restrictions on that line determine the cost of transmitting electricity from the point where it is generated to an LPC that is willing to purchase that power.

LPCs purchase electricity from either a single public utility or a wholesale power market. With a single public utility (e.g., Tennessee Valley Authority), the utility determines generation at each generating plant to minimize the cost of meeting load demand. With a wholesale power market, private generating companies make supply offers and an independent system operator (ISO) matches supply offers and LCP demand to maximize electricity generator and consumer net surplus. Unlike a public utility, an ISO does not have perfect information of the costs of generating electricity at a particular plant and does not have the ability to dictate generation at any plant. However, if private generating companies seek to minimize generation costs and ISOs have good information about the costs and technical constraints at each plant, a public utility can be viewed as both an ISO and a private generation company.

The agent-based model is composed of two separate submodules (see Figure 2). The first submodule is a modified version of AMES that accounts for electricity market forces. Market transactions occur on a daily time step. Each day D consists of 24 successive hours H=00,01,…,23 which allows for variation in electricity demand within the day. LPCs purchase electricity from the utility or wholesale power market on behalf of their end-use customers. Using actual supply offers for each generating plant and price-sensitive demand bids from each LPC, the utility or ISO selects hourly dispatch at each plant and LMPs to maximize the sume of producer and consumer surplus.



Generating Plants	Capacity (MW)
G1	1197
G2	465
G3	1561
G4	525
G5	468
G6	2470
G7	1576
G8	240
G9	1133
G10	1160
G11	1100
G12	155
G13	881

Local power company	Customers
LPC 1	408,411
LPC 2	372,249
LPC 3	200,477
LPC 4	174,529
LPC 5	163,649
LPC 6	197,759

Figure 1. Generating plans and local power company locations in a hypothetical electric grid

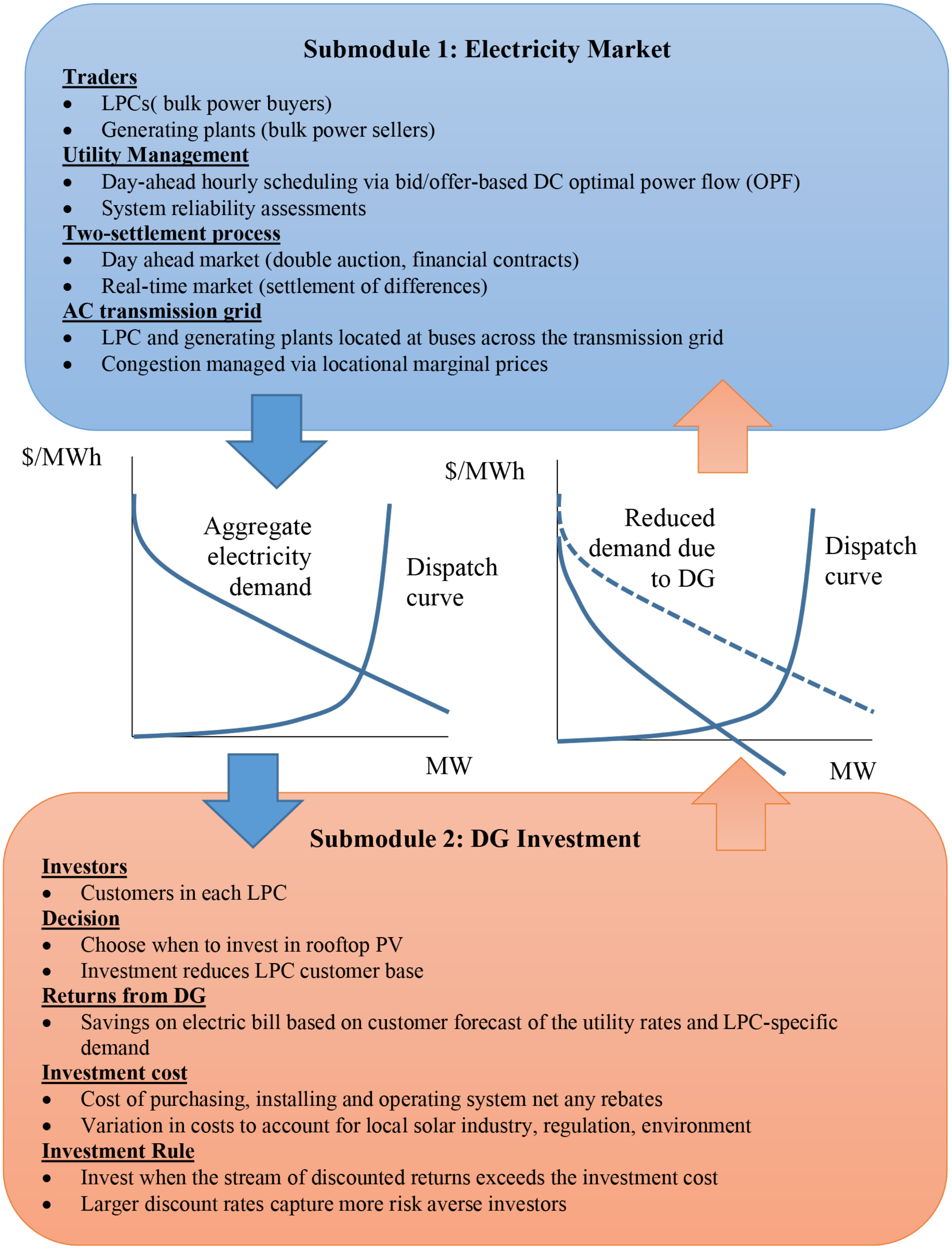


Figure 2. Conceptual representation of the agent-based computational economic model architecture

The second submodule accounts for the forward-looking DG investment decisions of the utility's customers. Our analysis focuses on PV systems because they account for more than 90% of installed DG in the U.S. Customers forecast future electricity rates and compare energy savings over the life of the PV system to the cost of the PV system investment. These costs include the cost of purchasing, installing, and operating a new PV system net of any rebates or tax incentives offered by the federal government or the utility. Customers choose to adopt a PV system according to a Marshallian investment rule. Specifically, customers choose to invest when the expected net present value of energy savings exceed the costs required to purchase, install, and operate the PV system.

The model considers four agent types: LPC operators, generators, grid managers, and LPC customers. These agent types reflect similar information, objectives, and motivations, although there may be considerable variation within an agent type. For example, each generator is an independent entity located at different points in the transmission grid with its own production technology, and production costs. Each LPC is located in a specific node of the grid with retail customers that are assumed to exhibit various degrees of price sensitivity. LPC customers do not participate directly in the wholesale electricity market but do choose when to invest in PV. LPC operators and generators are electricity market traders. The utility manages the wholesale power market subject to: (1) LPC scheduled demand, (2) generator supply offers, (3) thermal constraints on the transmission lines, and (4) node constraints that ensure supply equals demand.

Increased penetration of PV presents technical, economic, and regulatory challenges. A careful balance between production (generation) and consumption (load) is a prerequisite for a stable electricity grid. Grid operators must be aware of the accurate margin to instability for both the current and any foreseen credible system conditions. Grid operators (i.e., federal utilities or independent system operators; ISO) have to ensure the stability of the entire grid against any change anywhere within the grid as well as the impacts from any neighboring grid. Ever-growing penetration of intermittent energy resources such as DG changes the dynamic characteristics of the grid and makes daily efforts to coordinate generation and load more uncertain and challenging.

Economic challenges also arise when an electric utility finds a wholesale rate increase to be futile in raising sufficient revenue to cover the total costs of operation. Traditional electric utilities face high fixed costs due to the necessary investments in physical generation, transmission, and distribution infrastructure. Utilities often recover these fixed costs through volumetric rate structures. In response to increased installation of consumer-sited DG, utilities are forced to raise wholesale rates to ensure fixed cost recovery. Since consumers possess a downward sloping electricity demand curve, higher wholesale rates cause more consumers to invest in DG and energy efficiency measures, lowering wholesale sales volumes and triggering further rate increases on those customers that continue to rely on the grid for electricity. While the rate and extent of this self-perpetuating cycle must be determined on a utility-by-utility basis, this instability in electricity markets is determined by two factors: 1) the average price and marginal cost for electricity service and 2) the price elasticity of electricity demand facing the utility. In most states, customers have the right to sell surplus electricity from DG systems back to the utility (net metering). This can lead to more volatility in generation supply that requires generating units to ramp up and down quickly. This increased use of ramping units perpetuates the cycle as utilities are forced to charge higher rates in response to increased us of more costly ramping units.

3. 1. *Electricity Demand*

Each LPC is comprised of I_j customers which represents the sum of residential, commercial, and industrial customers. For each day *D*, the demand bid reported by LPC *j* for each hour *H* of the day-ahead market in day *D*+1 consists of the price sensitive-demand bid function

$$p_j = c_j - 2d_j\left(I_j\right)q_j\left(H\right) \tag{1}$$

where $0 \le q_j\left(H\right) \le \overline{q}_j$, in MWs, is the quantity purchased by the LPC and p_j is the maximum willingness to pay per MWh for $q_j(H)$. c_j and $d_j(I_j)$ are nonnegative.

The bid function in equation (1) implies the following relationship between per-capita electricity comsumption and electricity rates:

$$\frac{q_j}{I_j} = \frac{c_j}{I_j 2d_j\left(I_j\right)} - \frac{1}{I_j 2d_j\left(I_j\right)} p_j = y_j - x_j p_j \tag{2}$$

where $y_j = \frac{c_j}{I_j 2d_j\left(I_j\right)}$ and $x_j = \frac{1}{I_j 2d_j\left(I_j\right)}$. We used utility-level data on per-capita electricity consumption and electricity rates to estimate x_j and y_j for each LPC. Estimating demand parameters with a single equation (with quantity as the dependent variable and price as one of the independent variables) raises concerns about endogeneity. In this case, the endogeneity problem exists because price is determined by quantity and quantity is also a factor that impacts price. Estimated demand parameter would be inconsistent if the endogeneity of the price variable were ignored.

Following Halvorsen (1975) and Kamerschen and Porter (2004), a simultaneous supply and demand function model is used to estimate x_j and y_j for each LPC. The simultaneous approach is preferred because both price and quantity are identified and thus, endogeneity at the aggregate level is avoided. Three-stage least squares (3SLS) was used to account for endogeneity and correlation between errors in the two equations.

The demand equation assumes demand is a function of price and other environmental and economic variables and takes the following form:

$$Q = \alpha_1 + \alpha_2 P + \alpha_3 \ln X + \alpha_4 \ln G + \alpha_5 \ln CDD + \alpha_6 \ln S + \varepsilon \tag{3}$$

where ε is the error term and *Q* and *P* are average annual electricity usage per customer (MWh) and average electricity retail price ($/MWh), respectively. Other demand-related variables include: *X*, GDP of the state in which the LPC is located; *G*, average retail price of natural gas; *CDD*, annual cooling degree days; *S*, installed price of a solar panel.[4] Since demand should decrease as price of electricity goes up, α_2 is expected to be negative. Price of natural gas would impact

[4] Cooling degree days is the number of degrees a days' average temperature is above 65 degrees Fahrenheit. For example, if the days' average temperature is 80 degrees, its CDD is 15. HDD (heating degree days) was also considered but was not significant.

demand for electricity because natural gas is a substitute for electricity for cooking and heating. On average, customers would reduce their electricity usage and turn to natural gas if the price of natural gas declines. As suggested by the literature, income and weather are also important factors in determining electricity demand. Lastly, the price of solar panels explains demand for electricity because more customers will choose to supplement electricity from the grid with rooftop PV systems as the price of these systems declines.

The supply equation reflects the relationship between electricity rates, electricity demanded by customers and the cost required to generate electricity:

$$P = \beta_1 + \beta_2 Q + \beta_3 \ln L + \beta_4 \ln K + \beta_5 \ln F + v \tag{4}$$

P and *Q* represent the same variables as above and is the error term. *L* and *K* denote the cost of labor and capital incurred to generate electricity. Fuel costs are captured by *F* which is the average of the spot price of natural gas and the average price of coal delivered to electric power plants.

While our electricity grid is hypothetical, electricity demand is estimated based on annual aggregates from Tennessee between 1990 to 2014. Customer electricity usage (commercial, industrial and residential), average retail electricity price and natural gas retail price are from Energy Information Administration's (EIA) State Energy Profiles.[5] GDP for Tennessee is from the Bureau of Economic Analysis.[6] Cooling degree days for Tennessee was taken from the National Oceanic and Atmospheric Administration.[7] The cost of a solar panel is from Lawrence Berkeley National Laboratory's "Tracking the Sun" report.[8] Since the lab report only contained data from 1998 to 2014 and the available data fit a linear trend with R-squared of almost 94%, we used this linearity to predict cost of solar for 1990 to 1997. Cost of labor in the electricity industry was proxied by the average annual hourly earnings in manufacturing taken from the Bureau of Labor Statistics. Ten-year treasury constant maturity rate, a proxy for the cost of capital, was taken from Federal Reserve Economic Data (FRED). Price of coal delivered to the electric power sector is from EIA and spot price of natural gas was taken from FRED.[9] All prices as well as GPD were deflated by the GDP deflator (base year 2014).

The demand equation has a R-squared of 80%, the supply equation about 90%, and both equations are significant (large chi-squared, p=0.000). Retail electricity price is significant in determining quantify and vice versa, suggesting that the simultaneous approach is the right model to use. Table 1shows regression results for the demand equation since it is the focus of our analysis. As expected, demand for electricity declines when its price increases. Price elasticity of demand, calculated at the mean of price and quantity from the data, is -0.278. This is well within the plausible range of -0.1 to -0.8 for long term demand elasticity suggested in the literature (Lijesen, 2007). Not

[5] http://www.eia.gov/electricity/state/tennessee/index.cfm. Table 8.
[6] http://www.bea.gov/regional/docs/product/.
[7] NOAA National Centers for Environmental Information, Climate at a Glance: U.S. Time Series, published November 2016, retrieved November 24, 2016 from http://www.ncdc.noaa.gov/cag/.
[8] https://emp.lbl.gov/publications/tracking-sun-viii-installed-price.
[9] Spot price of natural gas is only available since 1993, so the first three observations were calculated by taking the average of the following three years' data for lack of a clear linear trend in the data.

surprisingly, the retail price of natural gas has the opposite effect: higher natural gas prices lead to more demand for its substitute electricity. CDD is an indicator for weather, and larger CDD means relatively more extreme weather for a particular year. So one would expect CDD has a positive effect on electricity usage as well. Somewhat surprisingly, the cost of solar is not significant. One reason could be that Tennessee has not yet experienced a significant adoption of rooftop PV systems.

Table 1. 3SLS regression results for the LPC demand equation

	Coefficient	Std. Err.	p value
Constant	57.43		
P	-0.11	0.243	0.000
ln*X*	-2.98	1.740	0.087
ln*G*	2.81	0.638	0.000
ln*CDD*	2.14	0.759	0.005
ln*S*	-1.02	1.111	0.927

The next step is to generate LPC-specific values for x_j and y_j in equation (2). Since estimation was based on annual state level data, x_j is the same for all LPCs. Specifically, x_j is the absolute value of the coefficient estimate for retail electricity price from the demand equation above converted to hours: $x_j = x = 0.1124/(365 \times 24)$. While demand elasticities may vary across the service area, a lack of household electricity usage data at the LPC level prevents us from accounting for this variation in electricity rate sensitivity. LPC data is available for CDD and GDP, so these two plus the 2014 state level price of natural gas were substituted into the estimated demand equation. Cost of solar dropped out because it was not significant. Then the combined intercept for each LPC is calculated as

$$y_j = \left(57.43 - 2.976 \ln X_j + 2.813 \ln G + 2.137 \ln CDD_j\right) / \left(365 \times 24\right)$$

It is straightforward to convert these parameter estimates to estimates for the LPC bid function: $c_j = \frac{y_j}{x_j}$ and $d_j\left(I_j\right) = \frac{1}{I_j 2x_j}$. These results a presented in Table 2.

Table 2. Hour 0 bid function parameters for local power companies

Local power company	c_j	$d_j(I_j)$
1	418.94	$38975/I_1$
2	402.43	$38975/I_2$
3	402.43	$38975/I_3$
4	442.38	$38975/I_4$
5	442.87	$38975/I_5$
6	427.59	$38975/I_6$

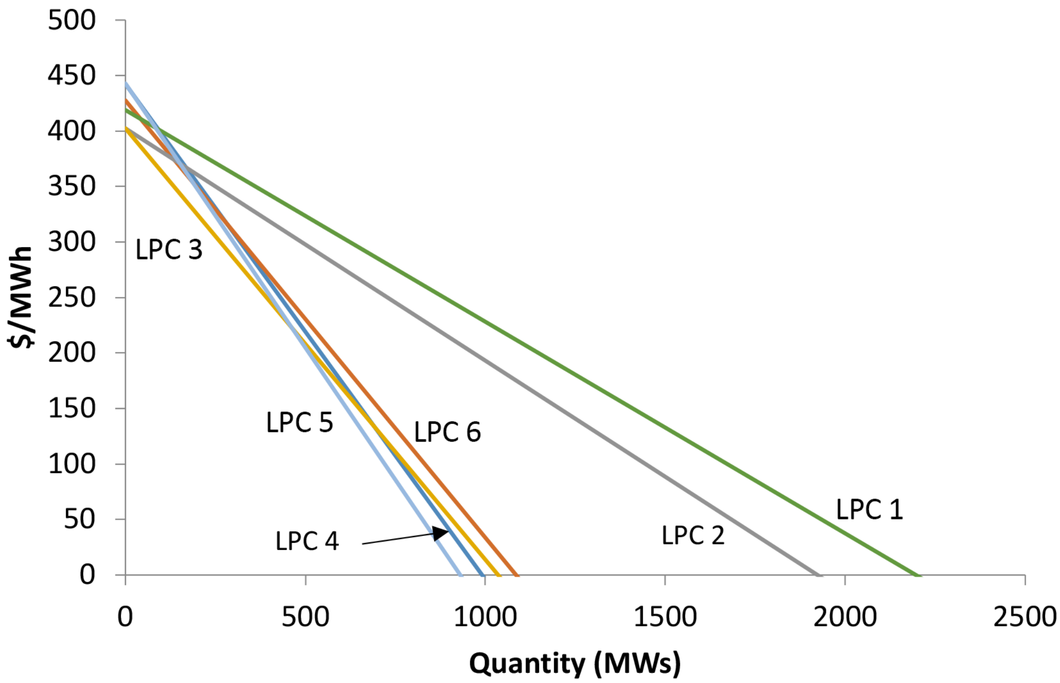


Figure 3. LPC demand at hour 0 before any DG-induced grid defections.

Unfortunately, a lack of within-day electricity use data prevents us from estimating observed patterns of lower electricity usage during the night and higher electricity usage during the day. To capture this within-day variability, we shift the electricity choke price (c_j) by hour according to Table 3. This assumes that quantity demanded varies between day and night but the price elasticity does not. For example, figure 4 shows the demand function for LPC 2 in the lowest demand hour (4 am) and highest demand hour (5 pm). Hourly shifts in the intercept might be expected if demand response to changes in electricity rates only arises through the extensive margin (changes in appliances).

Table 3. Hourly choke price for electricity (c_j)

Hour	LPC 1	LPC 2	LPC 3	LPC 4	LPC 5	LPC 6
0	418.94	402.43	402.43	442.38	442.87	427.59
1	384.03	368.89	368.89	405.51	405.96	391.96
2	363.08	348.77	348.77	383.39	383.82	370.58
3	356.10	342.06	342.06	376.02	376.44	363.45
4	342.13	328.65	328.65	361.28	361.68	349.20
5	349.12	335.36	335.36	368.65	369.06	356.32
6	356.10	342.06	342.06	376.02	376.44	363.45
7	377.05	362.19	362.19	398.14	398.58	384.83
8	425.92	409.13	409.13	449.75	450.25	434.71
9	467.82	449.38	449.38	493.99	494.54	477.47
10	481.78	462.79	462.79	508.73	509.30	491.73
11	488.76	469.50	469.50	516.11	516.68	498.85

12	495.75	476.21	476.21	523.48	524.06	505.98
13	509.71	489.62	489.62	538.23	538.82	520.23
14	509.71	489.62	489.62	538.23	538.82	520.23
15	516.69	496.33	496.33	545.60	546.21	527.36
16	523.68	503.03	503.03	552.97	553.59	534.49
17	530.66	509.74	509.74	560.35	560.97	541.61
18	516.69	496.33	496.33	545.60	546.21	527.36
19	509.71	489.62	489.62	538.23	538.82	520.23
20	502.73	482.91	482.91	530.85	531.44	513.11
21	495.75	476.21	476.21	523.48	524.06	505.98
22	460.83	442.67	442.67	486.62	487.16	470.35
23	425.92	409.13	409.13	449.75	450.25	434.71

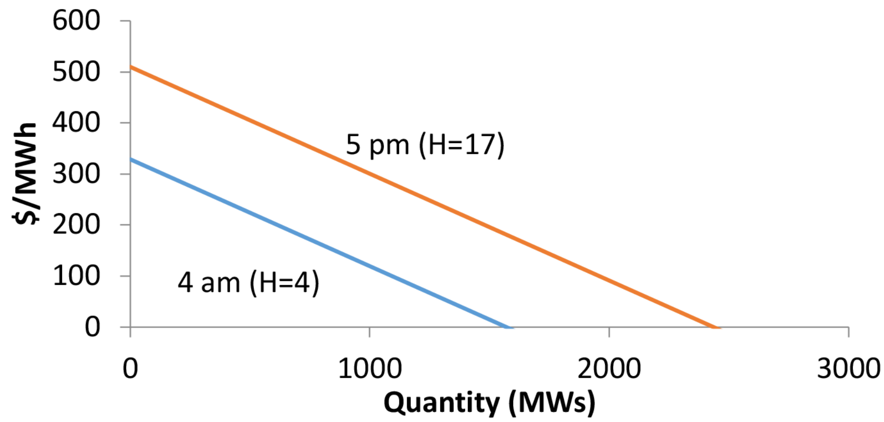


Figure 4. Electricity demand at low (4 am) and high (5 pm) demand hours for LPC 2

3. 2. Characterizing traditional generation and transmission

Each generating plant is characterized by a series of engineering and economic parameters specific to the combustion type and fuel used. These engineering and technical parameters are summarized in a nameplate capacity and a supply offer the represents the plant's marginal cost of supplying electricity. Following AMES, the supply offer reported by plant *i* for use in every hour of the day-ahead market for day *D*+1 consists of a reported marginal cost function

$$MC_i = a_i + 2b_i q_i\left(D\right) \quad (5)$$

where $0 \le q_i\left(D\right) \le \bar{q}_i$, in MWs, is the quantity of electricity supplied by plant *i* and MC_i is the minimum dollar payment plant *i* reports it is willing to accept (per MWh) for the electricity supply $q_i(D)$. The parameter values a_j and b_j are nonnegative.

Information on 13 generation plants includes: total number of units, per unit capacity (MW), total capacity (MW) and fuel type. Little information is publically available concerning generating units in Tennessee such as ramp rates, the minimum and maximum times the unit can operate, and the costs associate with generation. Instead, we randomly allocate fuel type a capacity to each generating unit in our hypothetical example. Krishnamurthy et al. (2016) summarized cost parameter ranges for generating units that used different types of fuel based on their capacity. Their study also contained detailed cost parameters used for all of their 76 generating units. We matched each of our generating units to one of theirs according to fuel type and capacity and then used information from Krishnamurthy et al. (2016) for our hypothetical generation parameters. A full description of parameter values for each generating plant is presented in Table 4. Supply offers for each generating plant are presented in Figure 5. Those plants with large intercepts like the natural gas units at GenCo 3 and GenCo 7 imply large fixed costs associated with generating electricity. Steeper supply curves such as the natural gas units at GenCo 1 imply a larger variable cost associated with increasing generation. The coal and nuclear plants are the low-cost generating units.

Table 4. Parameter values for generation assets

Plant	Fuel Type	Total Capacity (MW)	Min Up Time (hr)	Min Down Time (hr)	Ramp Rate (MW/hr)	Startup Cost ($)	No Load Cost ($)	Dispatch Cost Coefficient *a* ($/MWh)	Dispatch Cost Coefficient *b* ($/MW^2h)
GenCo 1	coal	741	8	16	120	18000	1215	18	0.00012
	NG	456	1	1	400	326	612.84	57.03	0.02133
	total	**1197**							
GenCo 2	NG	465	8	6	400	7250	250	56.5	0.008
GenCo 3	coal	428	8	8	120	5774	236.13	19.98	0.00167
	NG	1133	1	1	400	0	0	310	0.009
	total	**1561**							
GenCo 4	NG	525	24	24	400	25000	612.84	90	0.00292
GenCo 5	NG	468	6	6	400	7750	250	100	0.0075
GenCo 6	coal	2470	30	80	120	35000	3042	18.28	0.00012
GenCo 7	coal	976	8	16	120	13948	1210.5	18.2	0.00012
	NG	600	1	1	400	0	0	290	0.009
	total	**1576**							
GenCo 8	coal	240	8	16	120	16860	1212.98	18.1	0.00012
GenCo 9	nuclear	1133	24	48	120	900000	1250	10	0.00023
GenCo 10	nuclear	1160	24	49	120	950000	1500	10	0.0002
GenCo 11	nuclear	1100	24	47	120	850000	1000	11	0.00015
GenCo 12	coal	155	16	13	120	13873	744.69	18.4	0.00012
GenCo 13	coal	881	25	70	120	30000	2500	18.28	0.00012

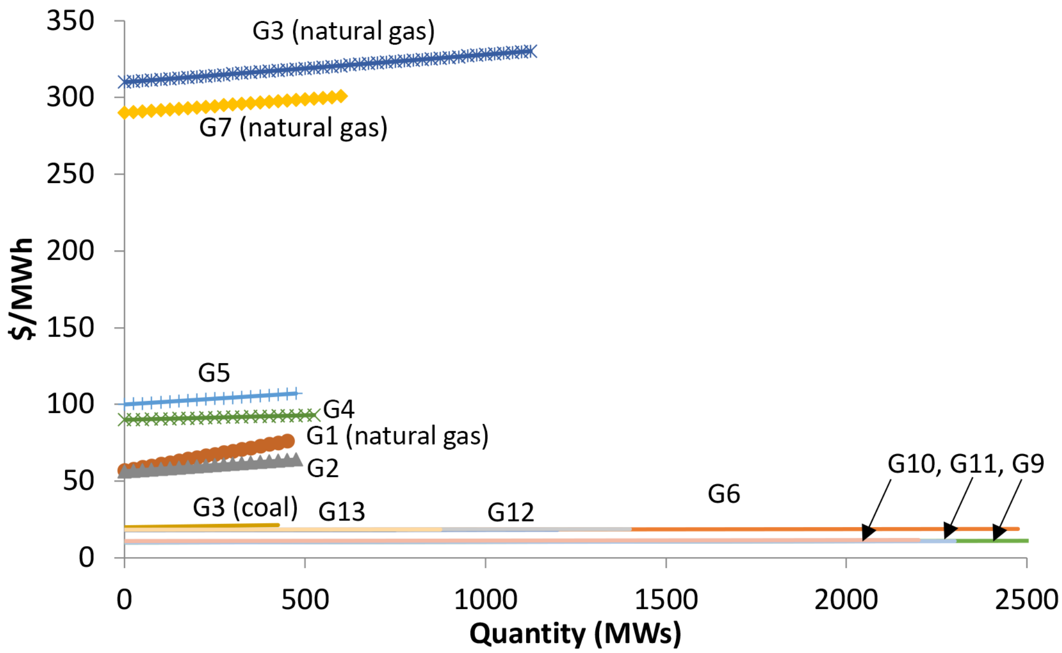


Figure 5. Generation plant supply offers

The transmission system links the different buses in the utility's network (see red lines in Figure 1) and accounts for temperature and voltage restrictions that constrain the utility's ability to balance load and generation. Following AMES, our model operates over a user-specified AC transmission grid characterized by the reactance and maximum capacity of each transmission line. For security reasons, little information is publically-available detailing a utility's transmission network. The stylized transmission network in Figure 1 is selected for exposition. The reactance for each line is estimated as a function of the shortest distance between two network buses. Following Krishnamurthy, Li, and Tesfatsion (2016), the maximum capacity for each transmission line is set at 10,000 MW. Transmission system parameters are presented in Table 5.

Table 5. Parameter values for the transmission system

Line	From Bus	To Bus	Distance (miles)	Resistance (ohms)	Reactance (ohms)	Max capacity (MW)
1	1	2	90	14.9	42.3	100000
2	2	3	130	21.6	61.1	100000
3	1	4	215	35.7	101.1	100000
4	3	4	115	19.1	54.1	100000
5	3	5	135	22.4	63.5	100000
6	3	6	180	29.9	84.6	100000
7	5	6	115	19.1	54.1	100000

3. 3. Accounting for distributed generation

All customers can purchase electricity from the utility at price *p* or switch to a rooftop PV system which requires an upfront, fixed cost investment but no marginal cost. For simplicity, assume the consumer is only considering solar systems large enough to completely offset their current electricity usage. Customers in each local utility choose to adopt the PV system based on a Marshallian investment rule. This investment rule suggests that customers will invest in solar when the stream of discounted energy bill savings exceeds the discounted cost of purchasing, installing, and operating the solar system.

The benefit of investing in DG is the expected net present value of electricity savings for the next 25 years (the length of a typical solar panel warranty). Since the consumer is able to completely fulfill electricity demand with this system, the benefit of the investment is the expected net present value of the utility's electric bills over 25 years. For simplicity, assume each customer in an LPC is identical such that individual electricity demand is given by $\hat{q}_j(H)=\frac{q_j(H)}{I_j}$. Rearranging the LPC bid function and substituting we find: $\hat{q}_j(H)=\frac{c_j(H)-p_j}{2d_j(I_j)I_j}$. Daily usage (in MW) by a customer in LPC *j* is: $\sum_{H=00}^{23}\left[\frac{c_j(H)p_j}{2d_j(I_j)I_{j0}}\right]$. The consumer expects electricity rates will increase at a rate of 1 percent annually implying that the customer's expectation of future electricity rates at $\tau>t$ is:

$$E_t\left[p_{\tau j}\right]=p_{\tau j}(1.01)^{\tau} \tag{6}$$

where is the electricity rate in LPC *j* at time *t*. Assuming energy demand and pricing is the same every day of the year, a consumer's annual electric bill is: $365\sum_{H=00}^{23} p_j\left[\frac{c_j(H)-p_j}{2d_j(I_j)I_j}\right]$.

For simplicity we assume there would be no change in the amount of electricity demanded regardless of whether the customer remains with the utility or supplies all electricity needs with their rooftop solar system. Then the residential energy savings from moving off the grid is the cost of grid-provided electricity over 25 years:

$$Savings_{tj}=\sum_{\tau=1}^{25}\frac{365\sum_{H=00}^{23} p_{tj}(1.01)^{\tau}\left[\frac{c_j(H)-p_{tj}(1.01)^{\tau}}{2d_j(I_j)I_j}\right]}{(1+r)^{\tau}} \tag{7}$$

where *r* is the discount rate used by the consumer. If the consumer could recoup the costs of the system in a secondary or scrap market, *r* would then be proxied by the relevant interest rate. Many papers have used 3%-5% for the customer's discount rate (Kildegaard and Wente 2015, Moradi et al. 2014, Garcia-Gusano et al. 2016, Fleten et al. 2007, Siddiqui and Marnay (2008).[10] If the consumer cannot recoup any of the costs of the solar system due to lack of a secondary (used) market for such technology, the real options literature suggests a higher discount rate should be used (Bauner and Crago 2015; Torani et al. 2016). This higher discount rate (hurdle rate or implied rate)

[10] Kubli and Ulli-Beer (2016) and Khalilpour and Vassallo (2015) use 2% and 7% respectively.

captures the investment's option value. Note that energy savings are a function of the customer base I_j and electricity rates p_{tj}. As the LPC customer base and electricity rates respond to increased adoption of PV systems, so too will the benefits of investing in PV systems.

We now turn to calculating the cost of a solar system. Customers in each LPC in Tennessee receive on average 5 hours of sunlight per day. So the AC output needed to cover 100 percent of electricity usage by a customer in LPC j is: $\sum_{H=00}^{23} \left[\frac{c_j(H)-p_j}{2d_j(I_j)I_j}\right]/5$. Buildings run on alternating current (AC) while solar panels produce direct current (DC). To convert AC demands into DC demands we divide by 0.8 to account for energy losses that arise from converting DC power to AC power. Thus the total solar investment needed to offset 100 percent of electricity usage in each LPC is: $K_{tj} = k_t \frac{\sum_{H=00}^{23} \left[\frac{c_j(H)-p_j}{2d_j(I_j)I_j}\right]}{5*0.8} * 1000000$ where k_t is the cost per watt of peak power (Wp) which includes system components, installation, labor, permits, inspection fees, and operational costs.[11] These costs have been declining over time causing more individuals to invest in DG but also causing individuals to choose larger systems (Barbose et al. 2015). Costs can also vary widely across individual solar projects. For example, among residential systems installed in 2014, roughly 20% of systems were priced below \$3.50/Wp while 20% were priced above \$5.30/Wp (Barbose et al. 2015). These trends are evident in the residential, commercial and industrial sectors.

To capture the declining trend and variability in solar costs, we treat the median installed cost per watt of peak power (as a log-normally distributed random variable with expected value and variance given by

$$E\left[k_t\right] = k_0 e^{\mu t} \tag{8}$$

$$Var\left[k_t\right] = k_0^2 e^{2\mu t}\left(e^{\sigma^2 t} - 1\right) \tag{9}$$

where k_0 is the current cost per watt of peak power, $\mu < 0$ is a constant parameter that captures the deterministic, declining trend in the cost of solar over time and σ is a constant parameter that accounts for the variance in solar costs experienced across customers in the utility's service area. For example, k_t may vary from customer to customer due to local availability of solar industry professionals, variation in solar generation potential due to roof aspect or presence of trees, or differences in hidden costs such as permitting and inspection that vary by local government. Equations (8) and (9) implicitly assume 1) the expected cost of solar is declining exponentially over time, 2) the range of solar costs customers experience increases as time passes, and 3) trends and variation in solar cost per watt of peak power does not vary between LPCs.

To estimate μ, σ, and k_0, we use the results of an annual survey on solar adoption conducted by the Lawrence Berkeley National Laboratory (Barbose et al. 2015). The LBNL solar survey

[11] For more information see http://energyinformative.org/solar-panels-cost/#case-study.

collected information on 400,000 residential and non-residential PV systems (excluding third-party owned systems) installed through year-end 2014. The data is self-reported by PV installers and represents 81% of all U.S. residential and non-residential PV capacity installed through 2014. Data collected includes number of systems, system size, customer type, installed price, module efficiency, and a select sample of state/utility rebates and performance-based incentive (PBI) payments.

Figure 6 presents trends in the median installed price of solar systems in six states (AZ, CA, CT, MA, NJ, NY) from 1998 through 2014. Median installed prices declined 6% to 12% per year depending on the customer segment. These declines are due to decreases in the price of solar modules and declines in soft costs (Barbose et al. 2015). Because k_t is log-normally distributed, μ and σ are the mean and standard deviation of the difference in logged values of median installed prices for residential systems: $\ln(k_t) - \ln(k_{t-1})$. k_0 is calculated as the average of the median installed prices across customer segments in 2014. This results in the following time-varying estimates for the expected value and variance of solar cost per watt of peak power: $E\left[k_t = 3.64e^{-0.0664t}\right]$ and $Var\left[k_t\right] = 3.64^2 e^{-0.133t}\left(e^{0.004t} - 1\right)$. These estimates of the mean and variance are used to calculate a forecast and 66% confidence interval for k_t from 2015 through 2040 (see Figure 6).

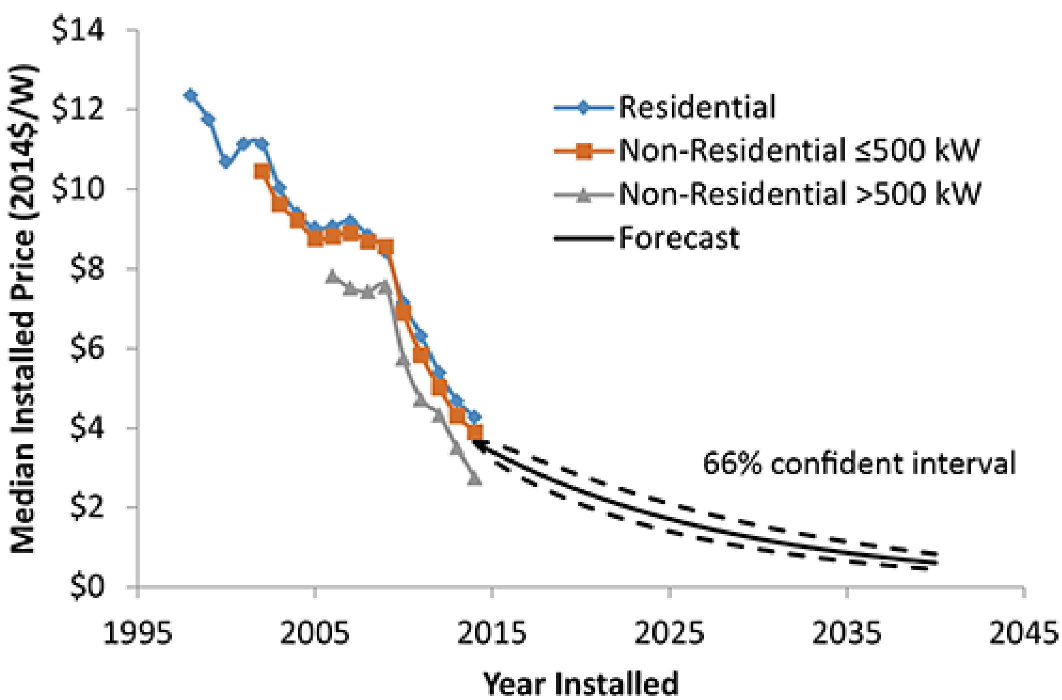


Figure 6. Historic Trends and Forecast in Median Installed Price of PV Systems.

At each point in time, each customer receives a random draw from the solar cost per watt distribution described above. The randomly drawn solar cost creates heterogeneity in the LPC that prevents all customers within the LPC from investing at the same time. For example, customer g in LPC j receives a random draw k_{tg} which results in a customer-specific measure of the solar investment cost K_{tjg} Customer g in LPC j will postpone investment in a rooftop PV system until

$Savings_{tj} > K_{tjg}$. If $Savings_{tj} > K_{tjg}$, the customer invests and the customer base in LPC *j* decreases by one. If $Savings_{tj} > K_{tjg}$, the customer does not invest and the customer base in LPC *j* is unchanged. This investment rule accounts empirical trends in the cost of solar DG systems that suggest increased adoption of solar PV systems in the service area in the near future. This investment rule also accounts for differences in customer demand across LPCs and in solar investment costs within LPC's. Both sources of heterogeneity ensure that the model predicts a gradual adoption of solar DG technology in the service area as opposed to a stair step investment track where all customers in the service area or within a single LPC adopt within the same year.

3. 4. Benchmark simulation results

This section presents results of a benchmark simulation from 2015 to 2039. Due to data limitations, the benchmark simulation results should be viewed as an illustrative example and should not be used for utility planning or policymaking. Total supply and demand in our hypothetical simulation in 2015 is presented in Figure 7. The demand curve illustrates the degree to which customers will curtail electricity usage in response to increased rates. Table 6 shows the quantity of electricity purchased by each LPC and the average LMP facing each LPC. LPC customers use approximately 5.5 kW per hour. According to the EIA, the average residential and commercial electricity customer in the U.S. uses 1.3 kW per hour and 8.8 kW per hour respectively. As expected, LPCs faced with a higher average LMP tend to purchase less electricity. In the absence of transmission line constraints, one would expect LMPs to be equal across the grid. Any spatial variation in LMPs would be eliminated as sellers seek to provide electricity to the area with the highest price (alternatively buyers would seek to purchase at the lowest price). Transmission constraints prevent sellers from being able to take advantage of price discrepancies (separation) across the grid. LPC 1 is faced with a high LMP due to congestion on the transmission lines feeding bus 1. Likewise, there is relatively little congestion on the lines feeding bus 3.

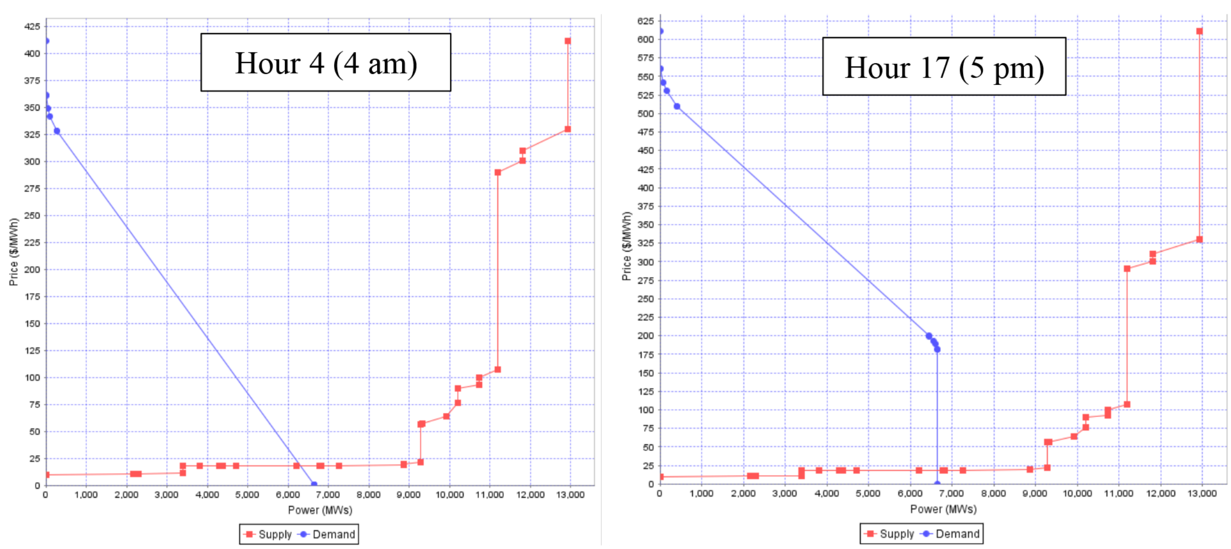


Figure 7. Total supply and demand curves at beginning of benchmark simulation

Table 6. Summary of LPC demand in benchmark simulation										
	% decrease in customers due to DG	Avg LMP ($/MWh)		Avg hourly power purchased (MW)		Avg hourly KW per customer		elasticity	
LPC		2015	2039	2015	2039	2015	2039	2015	2039
1	61.62%	$38.62	$14.63	756.30	178.27	1.85	0.97	0.26	0.41
2	64.51%	$25.45	$20.75	821.28	208.92	2.21	1.31	0.15	0.50
3	13.35%	$22.48	$14.09	1555.34	769.56	7.76	4.34	0.04	0.05
4	90.22%	$35.15	$22.40	924.28	832.15	5.30	23.03	0.09	0.06
5	63.34%	$27.44	$18.54	1867.70	866.33	11.41	11.60	0.03	0.04
6	88.64%	$36.59	$22.52	726.34	358.27	3.67	8.22	0.13	0.16

The supply or dispatch curve has a characteristic shape in which low cost generators such as nuclear and coal are responsible for generation along the flat portion of the curve with more expensive generating units taking over as the curve becomes steeper. Table 7 shows the dispatch and economic outcomes for each generating plant at the beginning of the benchmark scenario. Because supply intercepts demand at the flat part of the dispatch curve, only the low cost coal units and nuclear plants are generating electricity. GenCo 1, GenCo 3, GenCo 7, GenCo 9, GenCo 10 and GenCo 11 are all baseload plants in this hypothetical simulation since dispatch at these plants does not vary by time of day. GenCo 6, GenCo 12, and GenCo 13 serve as peaking plants since their dispatch increases during high-demand hours.

Table 7. Summary of generation in benchmark simulation						
	Annual capacity factor		Average daily net earnings		Average daily revenues	
Generating unit	2015	2039	2015	2039	2015	2039
GenCo 1 (coal)	99.81%	18.16%	$301,910	$14,232	$622,997	$72,583
GenCo 1 (natural gas)	0.00%	0.00%	$0	$0	$0	$0
GenCo 2	0.00%	0.00%	$0	$0	$0	$0
GenCo 3 (coal)	100.00%	30.49%	$162,951	$7,021	$375,527	$69,817
GenCo 3 (natural gas)	0.00%	0.00%	$0	$0	$0	$0
GenCo 4	0.00%	0.00%	$0	$0	$0	$0
GenCo 5	0.00%	0.00%	$0	$0	$0	$0
GenCo 6	55.54%	7.17%	$233,261	$10,374	$840,965	$87,440
GenCo 7 (coal)	75.05%	27.26%	$125,716	$16,548	$446,967	$133,144
GenCo 7 (natural gas)	0.00%	0.00%	$0	$0	$0	$0
GenCo 8	5.07%	0.00%	$716	$0	$6,005	$0
GenCo 9	100.00%	99.98%	$324,930	$100,939	$604,019	$379,979
GenCo 10	100.00%	99.99%	$792,722	$141,768	$1,077,581	$426,626
GenCo 11	44.14%	18.12%	$191,768	$43,026	$320,329	$95,701
GenCo 12	88.14%	2.51%	$29,764	$96	$90,473	$1,851
GenCo 13	51.23%	1.03%	$100,765	$176	$299,829	$4,270

As time passes in the simulation, cost per watt of solar generation falls according to the forecast in figure 6. This causes customers to invest in solar DG effectively separating them from the grid. Figure 8 shows simulated solar DG adoptions and the impact on LPC customer bases. Solar adoption initially arises in LPC 1, 4 and 6 service areas in 2022 and 2023. These areas are located on a part of the grid where congestion and LMPs are greatest. This congestion is driven in part by the relative lack of generation on this part of the grid. Customers in LPC 3 and 5 are relatively slow to adopt because their high electricity usage per customer implies a larger and more costly solar system would be needed to offset their electricity usage. These grid defections lead to drastic changes in the LPC customer base. By 2039, the customer base in LPC 4 and 6 drops by nearly 90 percent making them the smallest LPCs in the study. LPC 3 only shrinks by 13 percent making it the largest LPC in the state by 2039. LPC 5 moves from the sixth largest LPC in the area to the fourth largest by 2039.

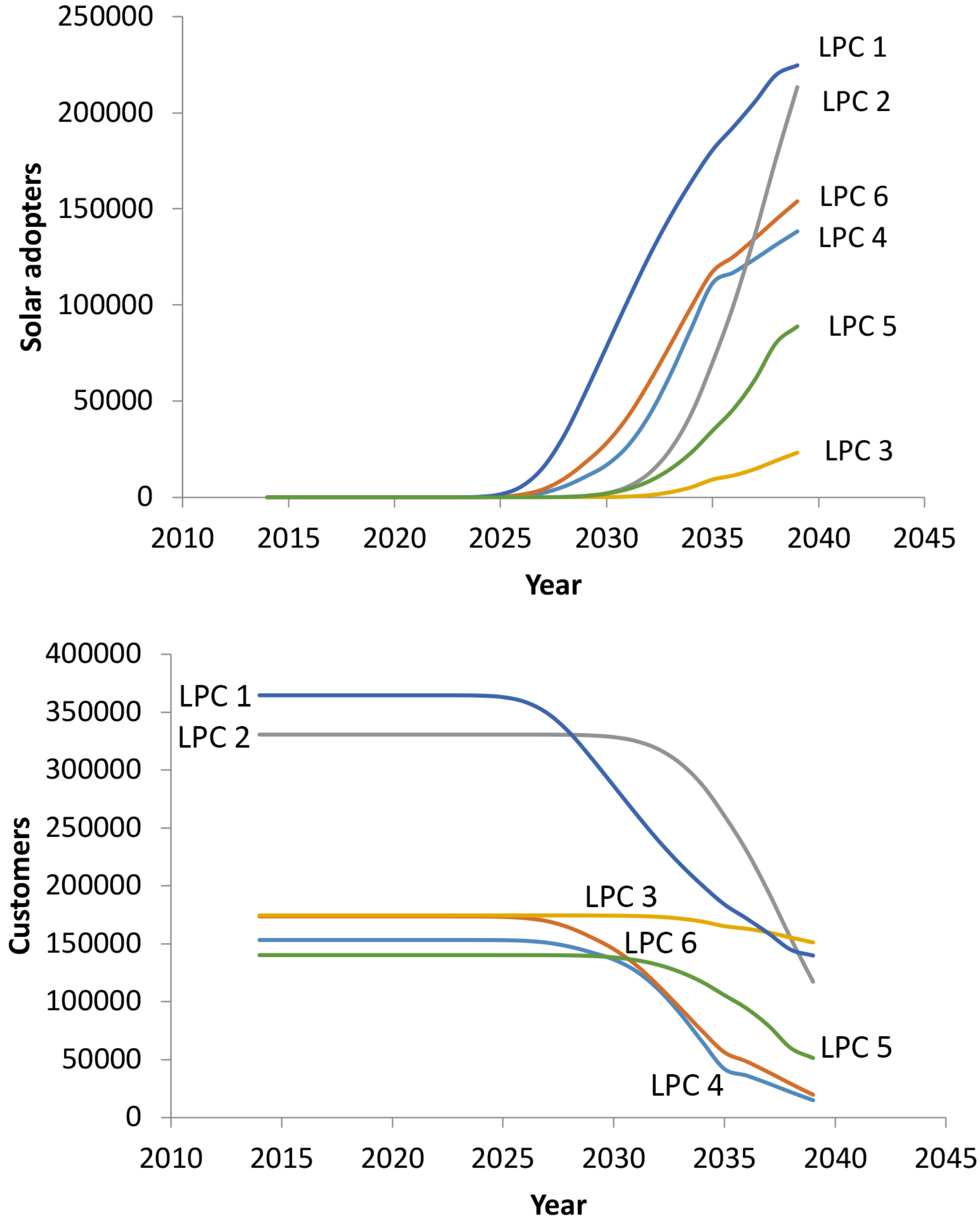


Figure 8. Simulated grid defections and declining LPC customer bases

As customers leave the grid, LPC demand begins to decline. More specifically, each LPC is willing to purchase less electricity at a given price. For example, Figure 9 shows the LPC demand curve for LPC 2 in 2014 and after nearly 65% of its customers invest in solar and leave the grid. This triggers changes in dispatch and LMPs across the grid. Figure 10 shows the changes in dispatch at each plant as customers begin adopting rooftop solar and leaving the local utilities. Declining demand triggers a decrease in dispatch at nearly all plants starting in 2026. GenCo 6 and GenCo 7 in bus 3 are the first plants to see lower generation. Because significant uptake of PV systems does not begin until after 2030 in LPC 2 and 3, generation decreases at GenCo 6 and GenCo 7 are due to decreases in demand at other parts of the grid such as LPC 1, 4 and 6 which see initial decreases in their customer base starting in 2026. While the marginal cost of generation is relatively low at these coal-fired plants, their no-load costs are high compared to other coal-fired plants like GenCo 3 and GenCo 12 which do not observe any persistent declines in generation until 2035 despite being located closer to areas where demand had drastically declined. Even the nuclear plant GenCo 11 at bus 6 begins to see declines in generation around 2026 which corresponds to declines in electricity demand in LPC 6. The only plants that do not see a decline in generation prior to 2039 are Genco 9 and GenCo 10. These nuclear plants benefit from a low marginal cost of generation and a low cost of transmission owing to their relative proximity to LPC 1 and 2.

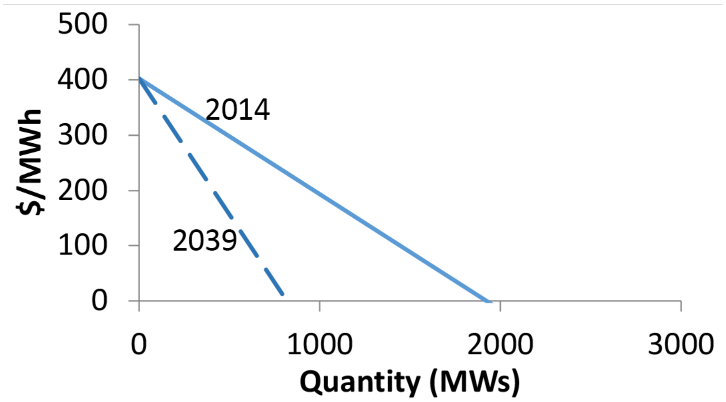


Figure 9. Electricity demand at H=0 before and after DG-induced grid defections in LPC 2

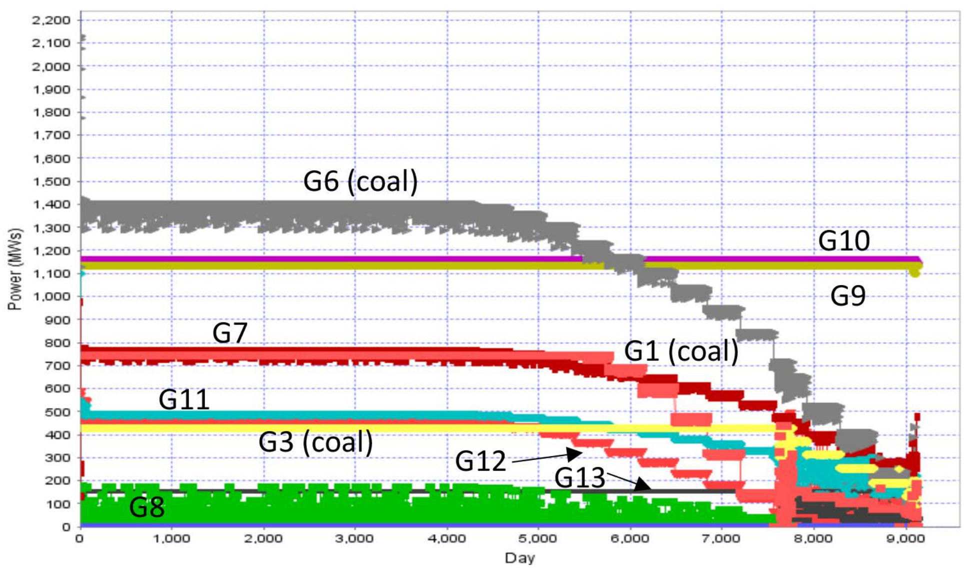


Figure 10. Impact of grid defections on generation at hour 17 in benchmark scenario

Figure 11 shows the changes in LMPs across the grid as customers begin adopting rooftop solar and dispatch responds to decreased demand. As expected, LMPs decline at all buses signaling a decline in line congestion due to the decrease in demand at the LPCs. More surprisingly is the differential impact of grid defections on line congestion. For example, the most dramatic decline in LMP occurs at bus 5 starting in 2026. Between 2014 and 2039, bus 5 transitions form the most congested to least congested parts of the transmission system. However, bus 5 is home to an LPC 5 that experienced a relatively mild decline in customers that didn't start until after 2030. The drastic decline in LMP at bus 5 is most likely due to the decreased demand in LPC 6 coupled with a decline in generation at bus 3. Despite the decrease in generation at bus 3, LMPs only decrease slightly due to the delayed and moderate uptake of PV systems at this bus and inflows of electricity from buses 2, 4, and 5.

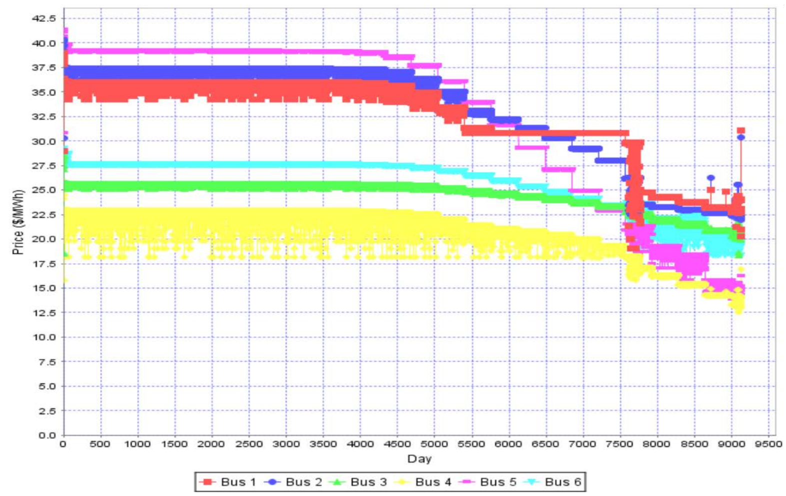


Figure 11. Impact of grid defections on hour 17 locational marginal price in benchmark scenario

3. 5. The influence of solar incentive programs

We compare the benchmark simulation results presented in section 3.4 to a counter-factual scenario with state/utility incentives that lower the cost of PV systems. The benchmark scenario presented in the previous section assumed customers did not take part in any state/utility incentive programs that would have lowered the realized cost per watt of solar generation. State/utility rebates and PBI payments for residential PV systems have ranged from 10 to 60 percent of the total cost of these systems (Barbose et al. 2015). The simulation experiment considered in this section investigates how the results in the benchmark simulation would change if customers participated in these programs. Figure 12 shows the realized cost per watt of solar PV systems from 1998-2014 and a forecast and 66% confidence interval. Realized cost is the difference between installed price and the pre-tax value of PV rebates and PBI payments (calculated on a present value basis). Cost per watt of solar generation is lower in this counterfactual scenario and still declines over time due to technological innovation and decreases in "soft costs" but not as quickly as in the benchmark scenario: $E\left[k_t\right]=3.21e^{-0.0514t}$ and $Var\left[k_t\right]=3.21^2e^{-0.103t}\left(e^{0.009t}-1\right)$.

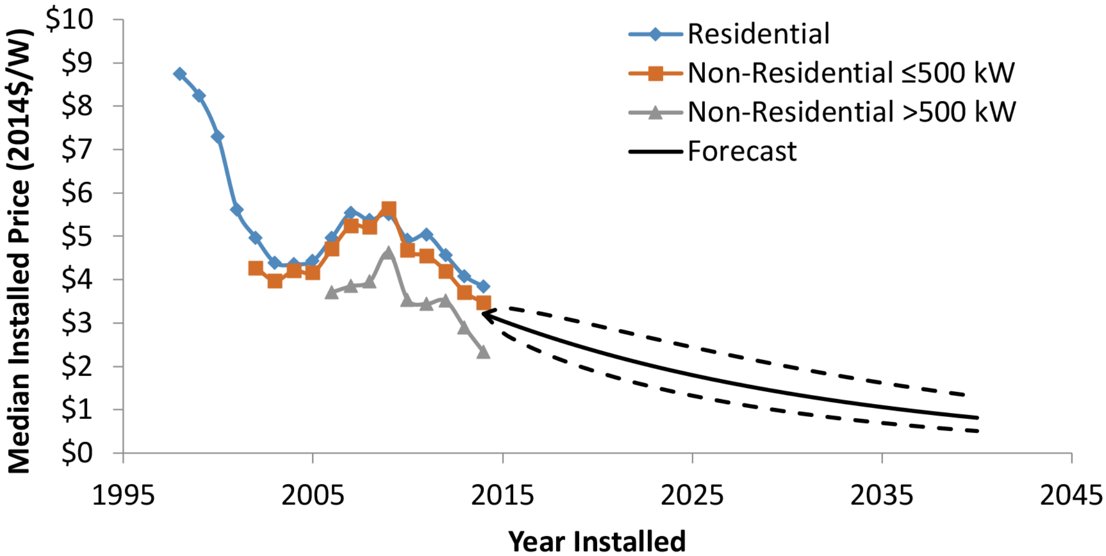


Figure 12. Historic Trends and Forecast in Median Realized Price (Installed Price – Incentive Payments) of Solar DG Systems.

Figure 13 shows simulated PV system adoptions and the impact on the LPC customer bases when customers take part in solar incentive programs. Much like the benchmark scenario, initial adoption of PV systems occurs in LPC 1 while customers in LPC 3 and 5 are relatively slow adopters. However, participation in solar PV incentive programs hastens the initial adoption of PV systems by 2 to 4 years in each LPC. By 2039, all LPCs experience a larger decline in their customer base when customers participate in solar incentive programs. The exception is LPC 4 and 6 which each see slightly less solar option between 2014 and 2039 when customers participate in the incentive programs (see Table 8).

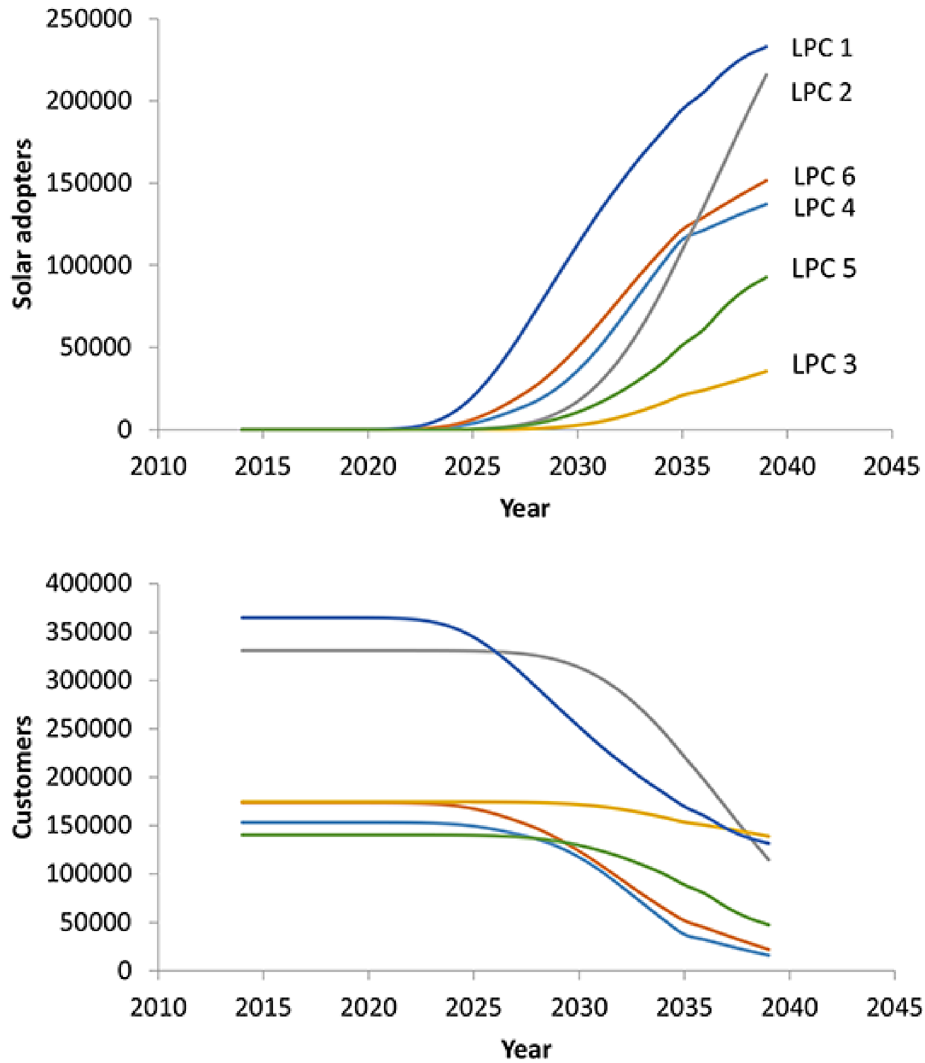


Figure 13. Simulated grid defections and declining LPC customer bases when customers take advantage of solar incentive programs

Why does a decline in the realized cost of solar generation (installation cost – incentive payments) lead to a decrease in solar adoption in LPC 4 and 6? The answer lies in understanding the countervailing effect of the incentive program on the utility's electric bills (the benefit of solar adoption). The solar incentive program lowers the demand for the utility's electricity. This implies a decrease in the electricity price facing LPCs *and* a decrease in the quantity purchased (Table 8). In most LPCs, the quantity purchased decreases less than the customer base triggering an increase in the electricity consumed per customer. This works to temper the decline in customer utility bills that arose from lower electricity prices. But in LPC 4 and 6, the quantity purchased decreases more than the customer base triggering a decrease in the electricity consumed per customer. The introduction of solar incentive programs works to lower customers' utility electric bills more than the customer base in these LPCs making solar adoption less attractive in these areas.

Table 8. Impact of solar DG incentive programs on LPCs in 2039								
	% decrease in customers due to DG		Avg LMP ($/MWh)		Avg hourly power purchased (MW)		Avg hourly KW per customer	
LPC	Without incentives (Benchmark)	With incentives	Without incentives (Benchmark)	With incentives	Without incentives (Benchmark)	With incentives	Without incentives (Benchmark)	With incentives
1	61.62%	63.88%	$14.63	$13.86	178.27	177.04	0.97	1.01
2	64.51%	65.26%	$20.75	$20.46	208.92	213.22	1.31	1.36
3	13.35%	20.33%	$14.09	$12.61	769.56	727.92	4.34	4.41
4	90.22%	89.45%	$22.40	$22.15	832.15	775.33	23.03	20.74
5	63.34%	66.04%	$18.54	$18.45	866.33	830.48	11.60	11.70
6	88.64%	87.24%	$22.52	$22.44	358.27	338.41	8.22	7.32

Similar trends in generation emerge when customers participate in solar incentive programs (see Figure 14 and Table 9). The primary effect of the solar incentive program is to hasten the decline in generation. Coal plants like GenCo 1, GenCo 6, GenCo 7, and GenCo 13 see generation begin to decline 2 to 4 years earlier with solar incentive programs than without. For other coal-fired plants like GenCo 3 and GenCo 12, the solar incentive program triggers minor changes in the timing of generation decreases. For most plants, the solar incentive programs cause a decline in plant-level revenues and net earnings (Table 9). This decline is due to the combination of lower LMPs and lower capacity factors. However, 2039 revenues and net earnings at GenCo 1 increase with customer participation in solar incentive programs. This is largely due to the more dramatic decrease in generation at GenCo 3 and GenCo 7 which makes generation at GenCo 1 more valuable in the later years of the simulation.

Table 9. Impact of solar DG incentive programs on 2039 generation						
	Annual capacity factor		Average daily net earnings		Average daily revenues	
Generating unit	Without incentives (Benchmark)	With incentives	Without incentives (Benchmark)	With incentives	Without incentives (Benchmark)	With incentives
GenCo 1 (coal)	18.16%	18.95%	$14,232	$14,603	$72,583	75,342
GenCo 3 (coal)	30.49%	24.35%	$7,021	$5,610	$69,817	56,097
GenCo 6	7.17%	4.45%	$10,374	$5,558	$87,440	53,799
GenCo 7 (coal)	27.26%	24.63%	$16,548	$13,553	$133,144	118,739
Genco 9	99.98%	99.18%	$100,939	$64,020	$379,979	340,764
GenCo 10	99.99%	99.95%	$141,768	$112,051	$426,626	396,759
GenCo 11	18.12%	15.96%	$43,026	$35,232	$95,701	81,669
GenCo 12	2.51%	1.38%	$96	$30	$1,851	976
GenCo 13	1.03%	0.56%	$176	$48	$4,270	2,233

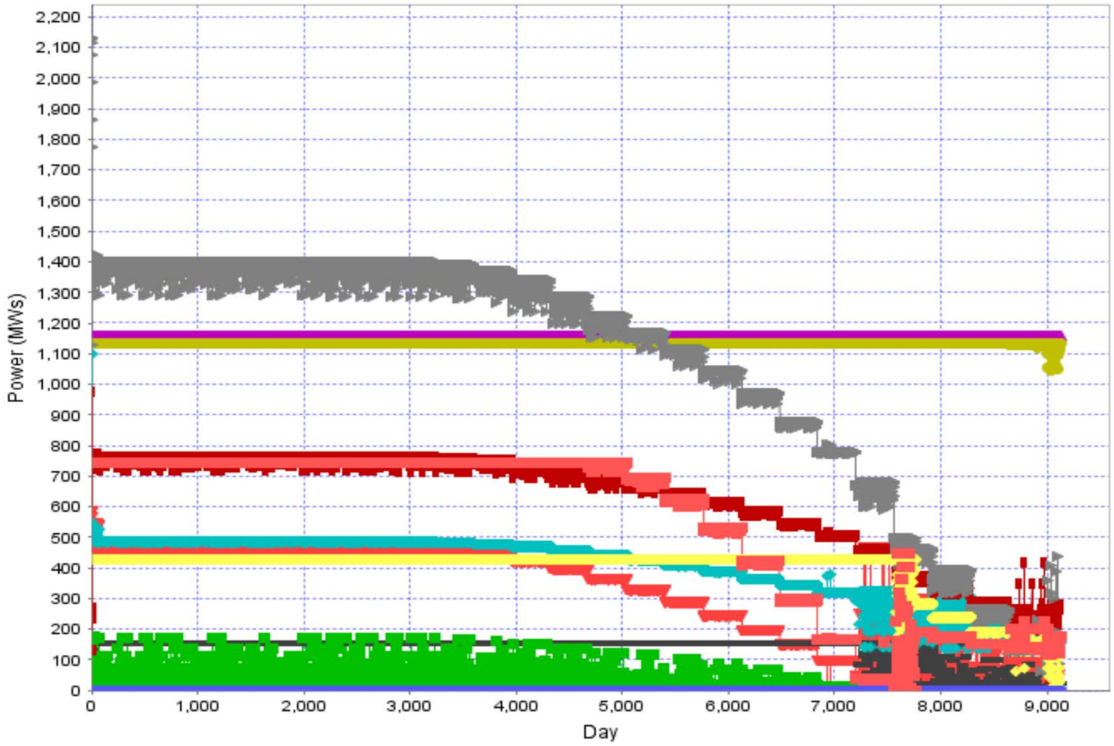


Figure 14. Impact of grid defections on generation at hour 17 when customers participate in solar incentive programs

4. FUTURE WORK

This report illustrates how agent-based computational economic modeling (ACE) can be used to investigate the dynamic response of a traditional electric grid in response to increased penetration of distributed solar generation. While these results are based on a hypothetical grid and should not be used to develop policy prescriptions, the model can easily accommodate data from utilities and LCPs that would allow the model to be used as a decision support tool. The model and computer program are flexible enough to easily generate a variety of simulation experiments. In this section we detail what we view as critical next steps required to transition this ACE framework into a decision support tool that could be used by utilities and ISOs to plan the transition from a centralized generation model to a decentralized generation model.

4. 1. Econometric treatment of simulation experiments

One of the hallmarks of agent-based computational economics is its ability to capture the complex dynamics that determine how many different micro-level processes translate into macro-level behavior such as electricity market performance or penetration of an emerging technology. However, one of the challenges of agent-based modeling is interpreting simulation dynamics and generalizing results. This remains true in our research. Idiosyncrasies of electricity demand at the LPC level interact with the physical nature of the generation and transmission system as well as the objectives and limitations of the utility's management to produce market level outcomes that would be difficult to predict from analyses that focused only on LPC demand (the micro level) or management (the macro level). However, drawing inferences and recommendations from these complex dynamic outcomes can be challenging. For example, it is unclear whether a decrease in generation at a particular plant is caused by an increase in solar adoption in a particular LPC or is simply correlated with solar adoption in that LPC. Recent advances in econometrics have improved economists ability to differentiate between correlation and causation. Techniques such as regression discontinuity and difference-in difference estimation are popular tools for natural experiments that seek to identify the effect of policy interventions in existing data. These techniques can be applied to our simulated data which would provide a more formal statistical analysis of the simulation experiments. This econometric treatment of simulation results can be critical for comparing simulation outcomes across different simulation experiments.

4. 2. Learning algorithm for the utility

The current version of the agent-based model assumes that the utility knows detailed information about electricity demand in each LPC. In other words, the optimal dispatch schedule for each generating unit presented in Figure 10 was identified by assuming the utility knew how much customers were willing to pay for centrally generated electricity. This would be a reasonable assumption in a world without cost-competitive solar technologies available to private customers since utilities likely tracks customer usage patterns over time. However, as the price of PV systems fall, customers may become more responsive to increases in electricity rates than they have been in the past (i.e., customer demand for traditional electricity may become more elastic in the future). Changes in customer price responsiveness will likely be unpredictable for the utility.

How should the utility adjust pricing and dispatch to respond to unpredictable changes in customer demand? To answer this question, this research activity would design and program a learning algorithm for management that would guide the behavior of the agents in the model. The learning algorithm would be based on learning algorithm developed for generation company agents in the AMES deregulated wholesale power market. In AMES, generation company agents cannot identify their optimal supply offer because they do not know the technologies and costs used by other (competing) generating agents or the LPC willingness to pay for electricity. At the end of each day, each generating agent uses stochastic reinforcement learning to update the probability that a particular supply offer will yield a return that is larger than expected. Stochastic reinforcement learning is rooted in the idea that the probability of choosing a particular action should increase (reinforced) if it yields a reward that is relatively good and decreased if it leads to an outcome that is relatively bad.

We will adapt the existing learning algorithm in AMES to better account for the uncertainties facing the utility and learning about the effect of DG on customer demand. Learning will take place with the management agent only. The utility's generating agents will report their true supply offers to management who makes dispatch and pricing decisions that accounts for 1) the more limited information officials have on customer demand and 2) the ability to engage in pricing and dispatch decisions that will allow the utility to learn about the nature of customer demand. VRE learning modules, a variant of a stochastic reinforcement learning algorithm developed using human subject experiments (Erev and Roth 1998), will be developed to control the learning process. The utility's agent learning module could easily be implemented within the existing model architecture by means of a free open-source *Java Reinforcement Learning Module* (Griesler 2005).

4. 3. Incorporate different wholesale pricing structures

Rate structures can vary across utilities. For instance, TVA currently charges the same residential, commercial, and industrial rates to all of its customers within its service area regardless of their location on the grid or the time of use. These fixed rate pricing structures shield consumers from the risk associated with hourly and daily variation in locational marginal prices. However, fixed rate structures can also cause significant efficiency losses (Borenstein 2005). Figure 15 illustrates how the differences in peak and off-peak demand illustrated in Figure 7 for LPC 2. Off-peak, the fixed rate is too high (and the quantity consumed is too low) but on-peak the fixed rate is too low (and the quantity consumed is too high). In each case, the shaded triangle shows the textbook description of the efficiency loss of fixed rates which do not reflect actual real-time prices. Greater penetration of DG can be expected to increase the difference between peak and off-peak demand and exacerbate the efficiency losses from fixed electricity rates. The so-called California "duck curve" illustrates how increased penetration of wind and solar in this state increases peak demand and decreases off-peak demand.

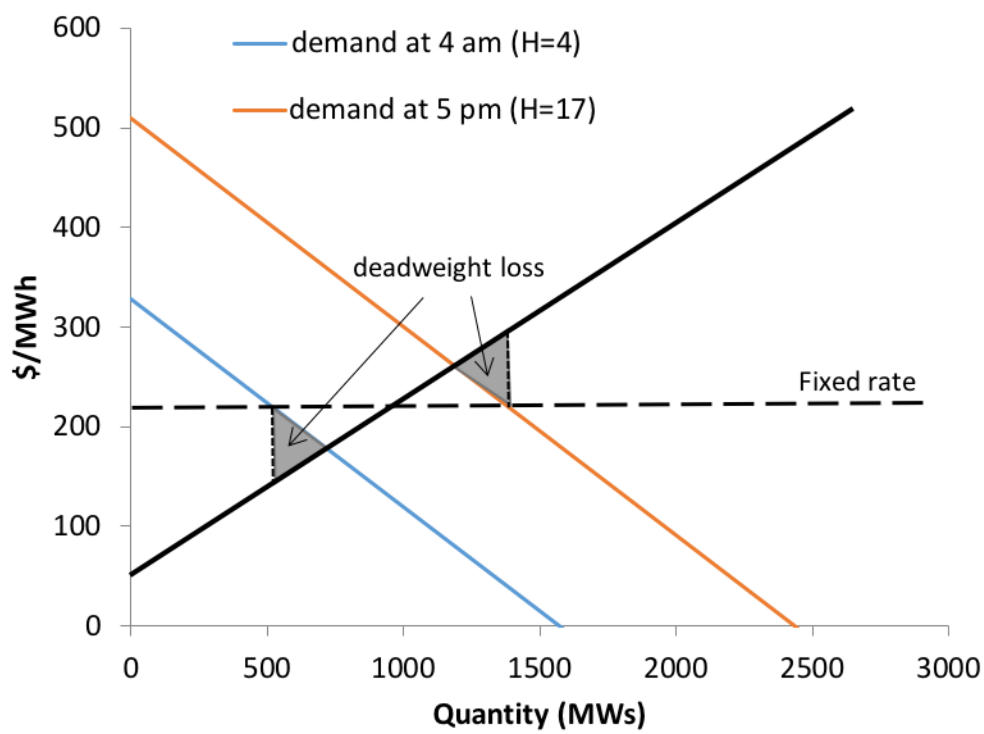


Figure 15. Economic inefficiencies caused by fixed electricity rates in LPC 2

It is unclear when and where efficiency losses may be exacerbated with TVA's current fixed rate structure. It is also unclear how fixed rate pricing may hasten or deter solar adoption. To address these questions, the locational marginal pricing mechanism in the current model will be adapted to consider a fixed rate structure. The spatial and dynamic aspects of our model allow us to adapt the model to consider pricing structures that vary over time and space. For instance, variants of the locational marginal pricing considered in this model account for how the cost of meeting load demand varies based on the location of generation and the transmission network. Time-of-use pricing structures (e.g., critical peak pricing and variable peak pricing) account for how the marginal cost of generation changes based on the time of day. A set of simulation experiments will be performed to show how 1) efficiency losses from TVA's current fixed rate pricing evolve over time in response to increased PV system penetration, 2) how fixed rate pricing influences PV system investment decisions, and 3) alternative pricing structures may provide efficiency improvements.

4. 4. Account for different customer types

Currently, the model combines residential, industrial, and commercial electricity customers. However, we know that the quantity needed, timing and intermittency of use, and incentives to invest in PV systems can differ from a residence to business to industrial facility. EIA currently collects information on these different user groups that would allow use to econometrically estimate demand functions for each user group. The LBNL survey also collects some information on installation costs, non-module costs, and average system size for residential and different sized non-residential systems that would allow use to investigate differences in PV system costs across these groups. Some industrial customers also have power purchase agreements with the utility or local utilities that may affect their decision to invest in PV systems. The computer code associated with LPC agents is only designed to account for a single agent type. Accounting for differences between customer types will require modifying the computer code associated with LPC agents to account for different customers types at the retail level.

4. 5. Investigate alternative customer investment scenarios

The DG investment decision currently considered in the model will be improved in two ways. First, the current investment decision represents an extreme scenario where customers completely separate from the grid by choosing PV systems capable of completely meeting their current electricity needs. For the vast majority of the utility's customers, completely separating from the traditional grid is not an option. Thus, the current model likely overstates the eventual decrease in electricity demand due to DG but underestimates the volatility in load created by increased penetration of DG. Accounting for intermittency in load demand and feed-in power will require two adjustments to the model. First, individual customer agent protocols would be adjusted to choose both the optimal size of a PV system and when to invest in a system of this size. This would allow customer agents to partially satisfy their electricity demand with power supplied by the utility. Second, LPC nodes in the transmission system model would need to be adjusted to allow for two-way power flows as customers with PV systems intermittently supply power back to the grid. This would effectively create two end-use customer agent types in the model: PV abstainers who are utility customers and PV adopters that are both utility customers and competitors by intermittently supplying power.

The second way the DG investment decision could be improved is by allowing for alternative investment rules. The Marshallian investment rule currently programed into the customer agent protocols is intuitively appealing and flexible but can be a poor predictor of PV system investment (Bauner and Crago 2015; Torani et al. 2016). Other alternative investment rules that will be explored will better account for risk and uncertainty (real options analysis) and empirical evidence that customer weigh losses more than gains in an investment setting (loss aversion).

5. CONCLUDING REMARKS

This report details ongoing efforts to adapt an existing agent-based modeling framework (AMES) for use as a decision support tool for utilities and independent system operators preparing to respond to increased penetration of DG in its service area. This report details two ways AMES has been adapted to make it more applicable to anticipated future conditions in the utility's service area. First, our model allows for customer electricity demand to be sensitive to electricity rates. One potential concern among utilities is the utility death spiral. As customers adopt DG, utilities are forced to raise rates to cover the large fixed capital costs associated with generation and transmission. Rate increases then increase the electricity costs associated with traditional electricity triggering more DG adoption. Customer demand in AMES is insensitive to electricity rates which exacerbates the utility death spiral. We use electricity sales data collected by EIA for the six largest utilities in the TVA service area to econometrically estimate TVA customer sensitivity to rate changes in each of the six largest utilities in the TVA service area. Second, our model creates a new end-use customer agent type that allows us to investigate DG investment behavior. Unlike AMES where customer demand is aggregated to the local utility level, our model disaggregates local utility demand to the individual customer level which will allow us to investigate how differences in socio-economics and information influence decisions to invest in DG and how these micro-level investment decisions influence macro-level outcomes such as dispatch and pricing.

Section 3.4 and 3.5 present model results without and with a solar incentive program. These results are intended to illustrate the capabilities of the model. However, additional research efforts are needed to ensure the model accurately captures the dynamic feedback loop between customer DG investment decisions and grid management. These additional research efforts are discussed in section 5.

While the results presented in this report are illustrative and not prescriptive, they do highlight a number of interesting trends. First, increased penetration of DG will have large impacts on dispatch at generating units and locational marginal prices. While other recent changes such as the retirement of coal-fired generation capacity can be expected to impact the cost of meeting existing load demand, the changes are arguably smaller than the impact of the 55-66% reduction in retail customers we observe in our simulations. Second, decreased load demand due to adoption of DG technologies will have a large impact on high-cost generating units in the system but may have little impact on the lowest-cost generating units. A result that emerges in all of our simulation experiments is that nuclear plants G9 and G10 experience little change in dispatch even with extreme decreases in the utility's customer base. We expect this result to persistent in future iterations of our research. Third, transmission line constraints matter. The physical nature of the transmission grid is often overlooked in economic analyses of DG impacts. However, transmission line constraints imply that the marginal cost of serving customers will vary across the utility's service area. This suggests that certain generating units and demand in certain LPCs will have a disproportional influence on the impacts of DG and the utility's ability to respond to increased penetration of

PV systems. For example, we observe far less PV adoption in LPC 3 even though its demand characteristics and customer base is similar to other LPCs such as LPC 4 and 6 located at other points in the transmission system. While further work is needed to better understand the influence of the transmission system, its importance in shaping the utility's ability to manage the increased penetration of DG is a persistent finding in all of our initial simulations.

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