Modeling Electricity Contract Choice: An Agent-Based Approach

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ABSTRACT

An agent-based modeling approach is used to model changes in contracts at the retail level, in the context of a distribution grid model. The distribution grid model is based on the IEEE 13-bus test case and contract choice is modeled using a modified Roth-Erev algorithm. The model focuses on residential contracts, the least price-responsive sector of the distribution system, but how this approach can be extended to commercial and industrial sector customers is discussed. The modeling results indicate what parameters are important in the decision to change contracts, and these parameters can adjusted to calibrate the model to empirical data. The results show that with these contract changes, the system is more responsive to peak prices.

Introduction

Agent-based Computational Economic (ACE) modeling structures autonomous economic agents and allows them to interact over time. Thus ACE models are "the computational study of economies studied as an evolving system of autonomous interacting agents." Tesfatsion (2003).

Much of the agent-based computational economic modeling directed at electricity markets has focused attention on the market connecting generators with aggregators or distribution utilities. This is a complex market deserving of considerable attention, but is not the focus of this report. Rather, we focus on contract arrangements that allow for price responsiveness at the distribution level to changes in electricity prices. We develop a model of a regime where the distribution utility offers alternative contracts to all its major accounts – residential, industrial, and commercial – that encourage more price responsiveness than would be the case where fixed-rate contracts rule. There is compelling logic that a price-responsive power system would be more efficient [Bohn *et al.* (1984), Hirst (2002), Caves *et al.* (2000)].

How can these retail accounts be motivated to move away from fixed-rate contracts? In this paper we document how such movements can be modeled; whereas our emphasis is on the residential customer, our approach could apply equally to commercial and industrial account holders. It is not expected that the retail customers will blindly adopt such options without first comparing the costs of their current loads under different pricing regimes and exploring the possibility of modifying their loads to take advantage of alternative pricing schemes. Consideration is given to the socioeconomic factors for the households, and factors such as building types for commercial users and load requirements for industry. We model this weighing of alternative contracts by retail customers within the context of a distribution system that properly accounts for the physics of distribution control. This distribution system is the Institute of Electrical and Electronic Engineer's (IEEE's) 13-bus test case, where 8 of

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the 13 busses are households, with 2 nodes at each of these 8 busses. These nodes can represent a variable number of houses. The 4 remaining nodes are currently empty, but we have modeled suppliers of electricity – distributed generation – and could use these nodes to model commercial buildings or industrial clients. While commercial and industrial accounts have not yet been added, the approach we take is general and only requires the addition of load profiles to allow their inclusion. Our discussion will focus on residential accounts, but we indicate how the model will be changed to cover the other retail accounts.

Our findings are preliminary but have intuitive appeal. When spot prices are above fixed-rate prices, households will almost always opt for the time-of-use (TOU) rate structure, because that allows for load shifting and hence reduced utility bills. (We assume that the costs of the real-time metering and communications equipment are bourn by the distribution utility and that utility gains accrue with improved price responsiveness through reduced utility risk.) The focus of this paper is on factors that affect the penetration of TOU contracts, with only a brief reference to real-time price (RTP) contracts. When spot prices are typically below the fixed rate and below the TOU rates, customers will first shift to the TOU rate, but will eventually shift to the real-time rate, adjusting load via a price-responsive controller (which, again, the utility subsidizes for the consumer). If spot prices fluctuate around the fixed rate, customers will opt for the TOU rates, again because the TOU rates always offer the opportunity to reduce utility bills. These results are preliminary for a number of reasons we later discuss, but in part because the data do not currently exist to calibrate behavior to market experience.

The paper is organized as follows. The next section summarizes what we can garner from the literature about how residential household respond to alternative pricing structures. Much of what is known is derived from experiments, not any sustained option set available to customers (at least to date). The third section describes the logic of the choice algorithm used by our residential agents to determine which contract to accept. This algorithm embeds a modified Roth-Erev choice logic that allows for experimentation, learning, and a scale effect. Our motivation for this choice is the report by Nicolaisen *et al.* (2001). The fourth section reports our simulation of the model over several years, allowing household agents to select contracts monthly. Over the course of the year, spot prices for our utility are usually above the fixed rate contract offered to households, thus precluding the switch to real-time price contracts. The level of these prices, along with the parametric factors that affect household choice, critically determine the choice of the contracts accepted by households. The fifth section details how this model will be expanded to include the commercial and industrial sectors. The final section puts these findings in context and outlines our continuing research agenda.

Household Response to Alternative Pricing Schemes

Previous studies on residential electricity contracts are scattered and rare. Most of the studies on consumer contract selection are based on experimental studies going back to the late 1980s, when energy prices were high and utilities were looking for ways to save energy and help the nation cope with economic consequences of the 1970s oil crises. With improved information and communications technology, interest has been revived, with experiments being conducted in Washington, Louisiana, Florida, and Pennsylvania within the last few years. While these studies have not all been completed, there is clearly an interest in exploring mechanisms by which consumers can be induced to move from fixed-rate contracts to those that are more price-responsive.

The typical contract for a household is a fixed-rate contract, with all energy consumption billed at a fixed per-kilowatt-hour charge (and often additional fixed charges). This contract form evolved despite the fact that the underlying costs of power production are determined by generation assets brought on-line as peaking requirements dictate. In part, this evolution likely occurred because the technology to meter residential use on a time-of-use basis was too expensive to deploy for all residential users and/or there was not an effective way to communicate changes in utility costs to consumers. Advances in information and communications technology, as well as the development of sophisticated controllers, now allow what was not feasible in the past. These developments allow for the possibility of residential consumers to have a choice of contracts, including fixed-rate, time-of-day rates, and real-time pricing of power used by the household.

Time-of-Use (TOU) Contract

Time-of-day or time-of-use contracts (hereafter TOU) are structured to allow different rates at different times that correspond to the time during the day when costs of power are higher. A variety of structures have been used, some with off-peak, shoulder, and peak prices; others with just off-peak and peak prices. The utility offers these prices to correspond to differential costs of power purchases and bills the customer based on use of electricity when the electricity is used. The advantages of the TOU contract include the simplicity of use to the consumer – who is aware of the costs throughout the day – and the advantage that the utility is now charging rates that reflect power purchase costs. Experiments that have applied TOU contracts generally find that consumers both shift loads to off-peak periods and also save on electricity use, although these results vary with the costs of implementation.

Train and Mehrez (1994) specify an econometric model of tariff choice and TOU consumption under optional TOU tariffs. The analysis suggests that the offering of the optional TOU rates did not dominate standard rates in a welfare sense. However, total surplus, excluding measurement costs, is estimated to have risen by \$1.41 to \$2.25 per month per customer who chose the TOU rates. Brian Pollom (2002) reported on Puget Sound Energy's (PSE) effort to increase customer awareness and responsiveness to TOU rates. A survey implemented by the company showed that 79% of residential customers and 70% of business customers took action to alter their energy use. Out of the residential customers who took action, 43% shifted *when* they used electricity without significant reduction in total usage; however, 41% reduced their usage significantly. Matsukawa *et al.* (2000) measured the effect of incentive payments on residential time-of-day (TOD) electricity demand in summer, using data from a residential TOD electricity pricing experiment in the Kyushu region of southern Japan. Results indicate that households shifted their electricity use from peak to off-peak periods in response to incentive payment. The evidence suggests that there is also a very strong relationship between household appliance holdings, number of people staying at home during the day, and outside temperature on the decision to make use of the incentives. Caves *et al.* (1989) defined TOU pricing as a popular rate program that offers utilities a more efficient pricing mechanism and a more efficient tool for load management in a 2-year voluntary TOU rate experiment carried out by Pacific Gas and Electric Company

(PG&E). Findings show that: participants in the voluntary program exhibited a significant response to TOU rates, reducing their on-peak usage share from 19% to 15%; that their responses depended on their appliance holdings and on the weather; and that voluntary customers had a substantially greater response than customers in prior mandatory TOU rate experiments. All of these studies suggest that TOU contracts can effectively shift load to off-peak periods and thus reduce both consumer bills and utility costs.

Real-Time Contract

A real-time price (RTP) contract for a residence would tie consumer prices to electricity prices paid by the utility, would change at least hourly, and would require communications between the residence and the utility. The price that the utility sees is established by the day-ahead future contract and real-time interaction between the generators, independent system operator (ISO), and utilities participating in the market. A consumer with a RTP contract would face the same prices that the distribution company sees, but would not have a binding quantity associated with the utility's contract. Rather, the utility would learn how customers would respond to price changes and would adjust their usage accordingly.

Bohn *et al.*. (1984), and Stoft (2002) described the underlying theoretical basics of the RTP process, while Aubin *et al.* (1995) reports on a French experiment. We rely on this theoretical discussion because there is little in the way of actual U. S. experiments with RTP at the residential level (at least within the last 70 years[2]).

At least three elements of enabling technologies would have to be present in order for RTP contracts to apply at the retail level: 1) communications devices that allow the announcement of the next hour's price; 2) a smart controller that can respond to these prices; and 3) a history of past market prices and use patterns so that the controller can learn to anticipate changes in prices over the day and seasonally. In the model we describe below, we assume these enabling technologies exist and are deployed as consumers request RTP contracts.

Contract Selection Algorithm

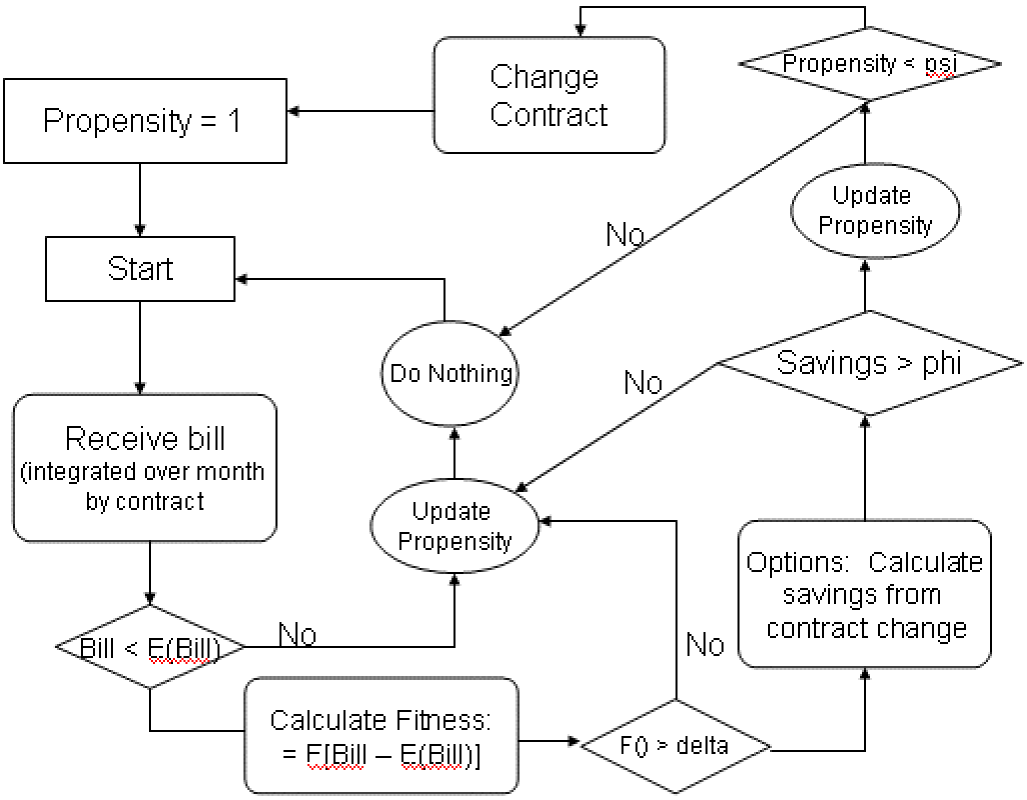
The mechanism of contract selection is described in Figure 1, below: Consumers receive a bill over an integrated period of time (for simplicity assumes this period is 1 month). Because consumers are different in their socioeconomic characteristics (income, age, family size, region and climatic zone of their residence, ownership of the home, etc.), they have different expected utility bills. Expected utility expenditures reflect the household (HH) consumption pattern that occurs as a result of differences in socio-economic characteristics. Consumers every month make a comparison between their expected electricity bill (based on weather patterns and known past consumption) and this month's integrated bill. If the integrated bill is less than the expected bill, the consumer will do nothing and wait till next month; otherwise the consumer will assess HH fitness, defined as the dollar value of the difference between the expected bill and the actual bill. If the fitness

[2] Stoft (2002, p. 14) points out that RTP (or a variant of it called the "Wright tariff") was used in this country in Chicago at the turn of the 20th Century.

measure of the consumer is less than some critical value, delta, the HH will do nothing. If the fitness metric exceeds delta, the HH will explore the options for switching contracts.

Options available include staying at the current contract or changing to a new type of contract. The criterion for type of contract selection is the saving that the consumer will gain from the switch, calculated from known RTP or TOU prices and modified consumption (i.e., modest load shifting to avoid peak rates, but the same total kWh usage). If anticipated saving is higher than some trigger level, phi, the HH will update their propensity to switch contracts, and if this value reaches a critical value, psi, switch from the existing contract to a new one; otherwise, the HH will do nothing.

Figure 1. Flow Diagram of Decision Logic for Contract Choice – Residential



If the HH chooses to switch from the current contract to another, they are constrained to move in a strict hierarchy. Starting at a fixed rate the HH can only move to a time-of-use contract. From a TOU contract, the HH can move to either a real-time price contract or return to a fixed rate contract. If RTP contract is selected, the HH can only move from RTP to TOU. This condition is imposed because it seems reasonable that the HH would not enter RTP contracts without some experience with TOU rates and because utilities would want to discourage movements back toward fixed rates.

At the core of a price-responsive retail electricity market that includes households is the decision to adopt a specific type of contract that has advantages to both the consumer and the distribution utility. The advantages to the utility come from sharing the risk of wholesale price fluctuations that affect the utility's costs; the advantages to the HH come from being able to manage its utility bills better and, with that better management, reduce utility costs in its budget. Our solution is analogous to the market for long-distance or wireless telephone communications. Alternative contracts provide different pricing structures for individual clients that can be conditioned to suit the needs of the client. One who travels widely will want service that is nation-wide; those that use their cell phone for emergencies only will want a very different service contract.

The major challenge is the development of a "fitness measure" that triggers a switch from one sort of contract to another. In most applications of agent-based computational economic (ACE) models, this fitness measure is the gain to the agent – in the work we have studied so far, this is the cost of power subtracted from revenues for the aggregator and sales minus cost for the generators. However, for the HH, when a new contract is accepted the HH has to migrate from the current pattern of use under the old contract to the new pattern of use under the new contract aided by incentives – in the form of technology to manage loads and lower power bills. The household has a propensity to make this contract choice.

The propensity affects whether a HH retains or alters its contract status and this propensity gets updated monthly. That propensity gets modified, based on a calculated fitness measure and other parameters described below. Even if bills are high and savings exceed the trigger levels, if this propensity to change contracts has not reached a critical value, no contract change will occur. So in addition to trigger values for the actual bill over the expected, and savings that exceed some critical value, propensity has to fall to a critical level before a contract change is undertaken. Consider a situation in which a consumer has two criteria, one for their fitness and the other one representing their saving as a result of the change of contract (which can be calculated by multiplying a revised load shape by the alternative contract price). Also, in each period each consumer can choose from among several strategies, among which is the choice of doing nothing. The initial propensity of a consumer to change its contract is set to one. The consumer's propensity to change contracts is influenced by how recently the HH has changed contracts (i.e., there is a reluctance to change frequently), but this tendency can be offset somewhat by a willingness to experiment with an alternative.

To formalize this, designate $q_n(t)$ as the propensity to change contract for consumer n in period t, which is initialized at 1 to start and each time an alternative contract is chosen. At the end of each period t, $t \geq 1$, the propensity that consumer n associates with changing the current contract is updated in accordance with the following rule:

$$q_n(t+1) = [1 - {'}]\, q_n(t) - E_n({'}\Omega, \text{fitness}) \qquad (1)$$

where $'$ is some value lying between 0 and 1 which is a *recency* or forgetting parameter, which acts as a gain on the propensities over time and $'\Omega$ is the *experimentation* parameter that permits the more rapid modification of the propensity to change contracts if the reward for doing so is high.

E_n ($'\Omega$, fitness), the modified fitness measure, takes one of two values. If the fitness metric is less than some nominal amount, delta, then E_n ($'\Omega$, fitness) = 0; otherwise, E_n ($'\Omega$, fitness) = $f_n(t)$ [$'\Omega$], where $f_n(t)$ is the fitness metric, defined for the current model to be

$$f_n(t) = [\{\text{Bill} - \text{delta}\}/E(\text{Bill})]\verb|^|2. \qquad (2)$$

This change to the modified Roth-Erev of Nicolaisen *et al.* (2001) reflects an environment where the choices by the households are binary. Either the HH retains the current contract or changes to a new contract. If the recency parameter is set to a low number, this reflects a reluctance on the part of the HH to switch contracts. However after a period of time, that reluctance fades and any opportunity to save money on a different contract leads to an alternative contract. The experimentation parameter, ′Ωϵ can operate to overcome this reluctance if the rewards are high or if the household is very experimental. In the absence of strong financial incentive to change contracts, the propensity will erode at a speed determined by the parameter ′ζ With three parameters to set or modify – recency, experimentation, and the propensity trigger value – and two minimum fitness and savings values, it is likely that this model can be calibrated to the acceptance of alternative contracts by households, based on what evidence is available or will become available in the future.

The contract switching for households is simulated within a Pacific Northwest National Laboratory (PNNL) developed C++ and MATLAB distribution system model, called the Power Distribution Simulation System (PDSS[3]). The Results section discusses the results obtained from running a number of experiments using PDSS. This paper focuses primarily on the adoption of TOU rates, with only passing interest in RTP contracts. The project's ultimate aim is modeling all the retail customers and the distribution utilities as part of a larger generation, transmission, and distribution system. The entire system will include generators, independent system operators, demand aggregators, and utilities as agents trading in a variety of markets.

Results

The PDSS model was simulated with bulk power costs of $40/MWh, 7% losses, a rate of return to the utility of 8%, and administrative costs of 12%. These parameters imply a spot basis for power of $50.8/MWh. The TOU pricing scheme was similar to the Gulf States Power (2002) program, with off-peak (OP) rates at $32/MWh (from 10 pm till 6 am), shoulder (S) rates of $45/MWh (from 6 to 10 am and from 8 to 10 pm), and peak rates (P) set at $90/MWh from 10 am to 8 pm. The capacity of the system was initially scaled to 0.8 MW for 100 homes. This scaling was used to rapidly determine the approximate fixed rate price, where fixed rate (FR) contracts and TOU contracts were in balance. At this small scale, the model could be simulated over a period of 15 years in about 3 minutes.

Table 1 reports the results of these initial simulations and later simulations where the capacity of the system was increased by a factor of 10, from 0.8 MW to 8 MW and from 100 houses to 1000 houses. The first seven simulations show the smaller scale model, the later simulations show the 8 MW model. When the FR price was set at $50/MWh (not shown on the table), TOU contracts penetrated so little that they were negligible (1 household out of 1000). Conversely, when the fixed rate contract was set at $58/MWh, all customers rapidly switched from FR to TOU contracts over about 3 months time (again, these results are not shown).

The first seven simulations vary the fixed rate price between $53.5 and $54.338/MWh and show how sensitive the terminal set of TOU contracts is to the fixed rate price. A balance between FR and TOU contracts occurs with a FR price of $53.8/MWh, with FR contracts and TOU contracts at exactly 50% after 12 years. Note that a 5% change in the

[3] This model is described in more detail in Guttromson, Chassin and Widegren (2003).

price (row three compared to row six) increases the TOU contract percentage 37%, while a dollar change increases the TOU contract percentage by 71%.

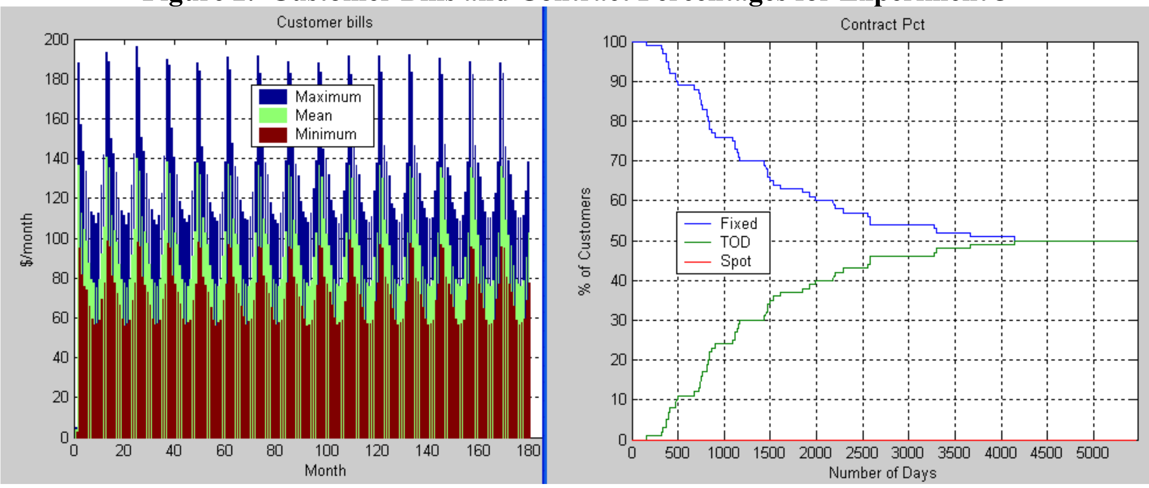
A graph of the balanced TOU and FR contracts 15-year results are shown in Figure 2. Note that transition between FR and TOU contracts shows monthly variation over the year as average contracts vary (right graph in Figure 2).

Table 1. Experiments with PDSS

Experi-ment	Bulk Price $/MWh	Capa-city MW	Fixed Rate $/MWh	TOU OP, S, P $/MWh	Roth-Erev parameters e, r, f,s#	Duration in months	TOU % at end
1	40	0.8	53.9	32, 45, 90	0.2, 0.1, 25, 25	180	64
2	40	0.8	53.85	32, 45, 90	0.2, 0.1, 25, 25	180	57
3	40	0.8	53.8	32, 45, 90	0.2, 0.1, 25, 25	180	50
4	40	0.8	53.5	32, 45, 90	0.2, 0.1, 25, 25	180	30
5	40	0.8	54.1	32, 45, 90	0.2, 0.1, 25, 25	180	76
6	40	0.8	54.338	32, 45, 90	0.2, 0.1, 25, 25	180	87
7	40	0.8	53.338	32, 45, 90	0.2, 0.1, 25, 25	180	16
8	40	8	53.8	32, 45, 90	0.2, 0.1, 25, 25	180	49.3
9	40	8	53.75	32, 45, 90	0.2, 0.1, 25, 25	180	50.
10	40	8	53.78	32, 45, 90	0.2, 0.1, 25, 25	180	49.3
11	40	8	53.78	32, 45, 90	0.2, 0.1, 25, 25	60	32.5
12	40	8	53. 8	32, 45, 90	0.2, 0.1, 25, 25	60	34.8

[1]# The letters represent: e = experimentation; r = recency, and f = fitness threshold, s = savings threshold.

Figure 2. Customer Bills and Contract Percentages for Experiment 3



When the model was run for 15 years at a larger size (8 MW, 1000 homes), the TOU contracts after 15 years were 49.3%. Lowering the price by 5 cents brought a terminal TOU contract percentage to 50%. The table also reports the results of runs for $53.78/MWh (used in Table 2) for both 180 and 60 months, and the results for 60 months using $53.8/MWh. The 2-cent difference makes virtually no difference to the outcome in either time period.

Table 2, below, shows results of systematically varying the Roth-Erev parameters in the model. At a $25 trigger point for both fitness and savings, the recency and experimentation parameters have little discernable effect. The terminal percentage of TOU contracts does not vary over this 60-month time period, though it might over a longer period.

Table 2. Simulations Varying Roth-Erev Parameters, Propensity Trigger at 0.3.

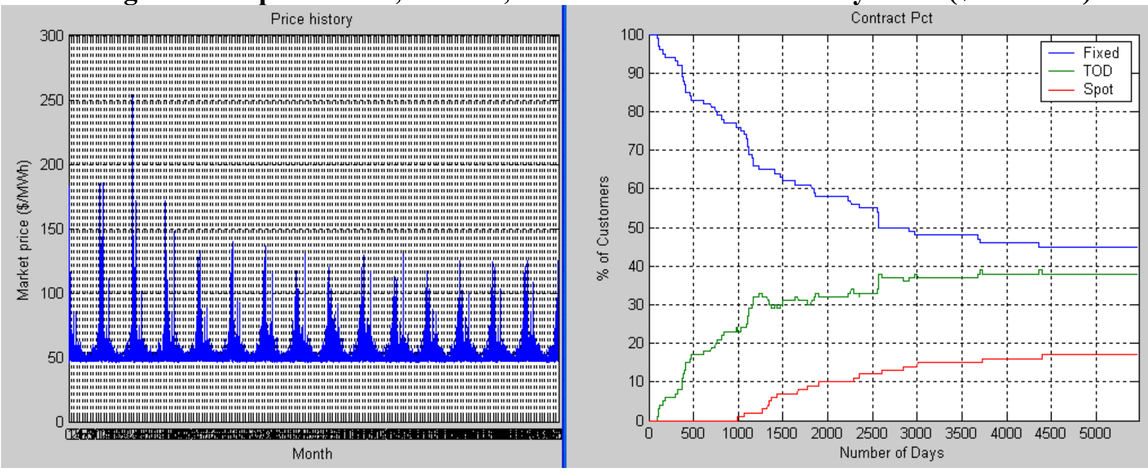
Experiment	Bulk Price $/MWh	Capacity MW	Fixed Rate $/MWh	TOU OP, S, P $/MWh	Roth-Erev parameters e, r, f, s*	Duration in months	TOU % at end
1	40	8	53.78	32, 45, 90	0.2, 0.1, 25, 25	60	32.5
2	40	8	53.78	32, 45, 90	0.9, 0.1, 25, 25	60	32.5
3	40	8	53.78	32, 45, 90	0.2, 0.9, 25, 25	60	32.5
4	40	8	53.78	32, 45, 90	0.9, 0.9, 25, 25	60	32.5
5	40	8	53.78	32, 45, 90	0.2, 0.1, 20, 20	60	37.2
6	40	8	53.78	32, 45, 90	0.9, 0.1, 20, 20	60	38.6
7	40	8	53.78	32, 45, 90	0.2, 0.9, 20, 20	60	38.6
8	40	8	53.78	32, 45, 90	0.9, 0.9, 20, 20	60	38.6
9	40	8	53.78	32, 45, 90	0.2, 0.1, 10, 20	60	37.2
10	40	8	53.78	32, 45, 90	0.2, 0.1, 20, 10	60	52.3
11	40	8	53.78	32, 45, 90	0.2, 0.1, 10, 10	60	52.3
12	40	8	53.78	32, 45, 90	0.9, 0.1, 10, 10	60	52.4
13	40	8	53.78	32, 45, 90	0.2, 0.9, 10, 10	60	52.4
14	40	8	53.78	32, 45, 90	0.9, 0.9, 10, 10	60	52.4
15	40	8	53.78	32, 45, 90	0.2, 0.1, 1, 10	60	52.8
16	40	8	53.78	32, 45, 90	0.2, 0.1, 10, 1	60	71.9
17	40	8	53.78	32, 45, 90	0.2, 0.1, 1, 1	60	79.6
18	40	8	53.78	32, 45, 90	0.9, 0.1, 1, 1	60	80.5
19	40	8	53.78	32, 45, 90	0.2, 0.9, 1, 1	60	80.5
20	40	8	53.78	32, 45, 90	0.9, 0.9, 1, 1	60	80.5

* The letters represent: e = experimentation; r = recency, and f = fitness threshold limit.

When both the fitness and savings triggers are reduced to $20, we now see a slight increase in the terminal TOU contract after 5 years, but the sensitivity of this change to variations in the experimentation and recency parameters is modest, at best. It is clear from experiments 9 and 10 that the most important trigger is the savings trigger. If this value is lowered to $10, the percentage of TOU contracts after 60 months jumps from 37.2 to 52.3. But even at this level, there appears to be little sensitivity to the other Roth-Erev parameters. At very low fitness and savings triggers, there is some sensitivity to the Roth-Erev parameters but, again, there seems to be a limit on the increase to the TOU contracts.

To demonstrate that these contract changes have an effect on the system price, Figure 3, below, reports on a long-term simulation (180 months) of the small version of the model, with a reduction of the bulk electricity price from $40 used elsewhere to $35/MWh.

Figure 3. Experiment 3, Table 1, with Lower Bulk Electricity Price ($35/MWh)



At this bulk price, the spot basis is at $44.45/MWh, well below the fixed rate of $53.8/MWh. Other than this change, the simulation replicates experiment 3 shown in Table 1. As a result of this lower bulk price, real-time price contracts penetrate the market, reaching an equilibrium of 17% of the total contracts, while TOU contract are at 38% and FR contracts at 45%. The left panel of Figure 3 reports the system price history over 15 years. The impact of the penetration of these price sensitive contracts shows up clearly in the price history, as peak winter prices decline over the years. There is very little decline in the second half of the simulation because there is little change in the contract structure after that time.

Considerations for Integrating Industrial and Commercial Accounts

We have demonstrated that a retail ACE model can be structured to allow the choice of alternative contracts with a distribution utility, using a TOU rate program for residential customers similar to one currently being implemented by Gulf States Power in Louisiana. We have changed the modified Roth-Erev algorithm of Nicolaisen *et al*. (2000) to fit the binary choice between alternative contracts that the household can accept. We find that the choice logic is highly sensitive to savings and fitness thresholds and less sensitive to changes in the experimentation and recency parameters of Roth-Erev. The results reported emphasize the choice between TOU and FR contracts, although Figure 3 also shows that RTP contracts will penetrate under specific pricing scenarios. We argued earlier that the modeling technique is general and would allow other retail customers. We build that case here.

For the commercial customer, the carry-over is obvious; it is less obvious for industrial customers. Households are modeled with thermal and non-thermal loads. The thermal loads are estimated using a differential equation model and thermostat setting where settings are adjusted based on prices, and these loads replicate metered loads from Northwest homes. The non-thermal loads are modeled probabilistically, to meet metered load shapes, with prices allowing a delay in the use of these appliances – Guttromson *et al.* (2003). Exactly the same strategy could be used for commercial buildings, with the thermal and non-thermal loads patterned to meet metered load data.

Metered loads from industrial plants could also be used to model the industrial customers, as with the non-thermal loads for commercial and residential customers, which would be the simplest approach. Most of industry uses electricity primarily for motors and lights; these are non-thermal loads that, with metered data, could be matched with load shapes just as is done with non-thermal loads in households. Where industries have substantial thermal loads met by electricity (food processing, primary metals), the differential equation approach would work well for thermostatic controls, again as with residential customers, except for the scale of energy use. Electric arc furnaces and other heating applications of electricity in industry are more kin to non-thermal loads and could be matched with load shapes probabilistically. What would be different for industry would be the nature of the contract (more on this below), and the ability of some industry to provide its own power through combined heat and power (CHP). We have simulated PDSS with distributed generation, but have not yet linked this to industrial loads.

Industrial customers of distribution utilities are usually faced with a contract that charges for energy with an additional charge for capacity (we ignore special contracts, such as interruptible rate contracts). Part of what precludes industry from being more price-responsive to changes in system costs is the fact that the capacity charge is not tied to peak prices for the distribution utility, except coincidentally. A pricing scheme for industrial and commercial customers that would more effectively pass on the systems costs, and thus make these customers more price-responsive, would be similar to the RTP contracts for residential customers.

Another way to model electricity use in industry would be to allow it to bid for power similar to an aggregator that purchases power for distribution utilities. Output requirements and load shapes would be critical components of this model, with fall-back power supplied by its own facilities or through contracts with independent power producers. While this would solve the problem of the contract structure, it would not abrogate the need for matching load shapes for specific industry.

Future Research

The integrated residential market choice model and 13-bus IEEE test case, PDSS, demonstrates the characteristics of a price responsive distribution system that allows customers to vary loads in response to prices. But there remains much to be done. The work currently in process falls under three topics: improving the current version of the model; broadening the retail market characterization to include commercial and industrial accounts; and integrating the distribution network into the larger grid. Of these three, integrating the distribution network into the larger system would allow a complete representation of a grid and could thus begin to answer some questions about the interactive system that otherwise cannot be answered. Broadening the retail market characterization, to include commercial and industrial end-users as well as adding advanced characterization of households, would add realism to the system that currently is not there. An obvious improvement to the current model would include experimenting with alternative formulations of the Roth-Erev algorithm. Work on all these fronts is proceeding.

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