

The Effects of Residential Real-Time Pricing Contracts on Transco Loads, Pricing, and Profitability: Simulations using the N-ABLE™ Agent-Based Model

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Abstract

An agent-based model is constructed in which a demand aggregator sells both uniform-price and real-time price (RTP) contracts to households as means for adding price elasticity in residential power use sectors, particularly during peak-price hours of the day. Simulations suggest that RTP contracts help a demand aggregator (1) shift its long-term contracts toward off-peak hours, thereby reducing its cost of power and (2) increase its short-run profits by being one of the first aggregators to have large numbers of RTP contracts; but (3) create susceptibilities to short-term market pressures and their coincident prices.

Key words: Real-Time Pricing, Electric Power Market, Market Redesign,
Agent-Based Model

JEL classifications: Q41, D13, D40

1 Introduction

Restructuring of the markets for electric power has led to occasional, yet substantial increases in average market clearing price, where the clearing price is

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significantly higher than the cost of producing the power. Profit opportunities in the spot market are sometimes large enough that, where contractually allowed, generating companies (Gencos) have foregone long term, fixed-price contracts with their customers to instead sell power in highly lucrative short-term markets. Additionally, Gencos have withheld production to create market shortages that drive up market price (See Federal Energy Regulatory Commission (2002), Brobeck (2002), Yoder and Hall (2000), Yoder and Hall (2002)), and industrial customers with long-term contracts have stopped production and sold their contracts for large profits.

Demand aggregators (or Transcos) and the households they serve have few options for responding to these short-run increases in price — short-run and long-run contracts in electric power markets operate in a manner that makes residential power use essentially inelastic in the short run to price changes. Furthermore, demand aggregators must be economic *price takers* in the very short-term, that is, they must respond rapidly to external, largely uncontrollable price and quantity changes. To introduce residential demand-side price elasticity to the market, the power industry has proposed a number of new residential contracts, such as *real-time pricing* (RTP), where demand aggregators charge prices that more closely reflect the cost of electricity during the particular time of usage,² and *interruptible-demand* contracts, where power demand aggregators offer a lower rate to a customer but reserve the right to cut the customer's power during peak-load hours. With either type of contract, during high-price periods the residential sector responds to peak-hour prices with lower demand, i.e., their demand is *price elastic*.

While these contracts may be designed to increase overall efficiency, the individual incentives of the power demand aggregators that offer the contracts may create new economic instabilities. To investigate some of the potential price, load, and profitability dynamics and instabilities created by these demand-management policies, we construct a multi-period model in which a demand aggregator offers real-time price contracts to its residential customers. The residential sector is modeled with a highly disaggregated collection of households, who purchase either uniform price contracts or real-time pricing contracts. Households using electricity under a real-time pricing contract actively decide whether to reschedule their daily use of power, based on their individual budgets, their personal tolerance for the inconvenience caused by the rescheduling, their willingness to experiment with an RTP contract, and the social acceptance of these new contracts.

Our power demand aggregator has several, sometimes conflicting, business objectives: first, it must be able to charge prices for both contracts that keep it

² These prices are typically high during periods of peak usage, when the less efficient, higher-cost generators are brought on-line to meet short-term high demand.

solvent and maintain reliability of that solvency. Second, it would like significant numbers of customers to use RTP contracts and reschedule their demand to off-peak hours; this decreases its average cost of power and increases the amount of excess transmission capacity it can sell in short-term, highly profitable transmission markets. Third, it needs to prevent any unexpected, large increases in peak-hour power use by its customers, since unexpected purchasing of additional peak-load power can be very expensive.

The simulations are constructed from two separate Sandia models: (1) the residential, commercial, and industrial use sectors, using the NISAC³ Agent-Based Laboratory for Economics (N-ABLE); and (b) the power generation sector, a Java-based simulation running on a separate computer platform. The two models are synchronized to the current simulation day and exchange data using Simple Object Access Protocol (SOAP) bound to Hypertext Transfer Protocol (HTTP).⁴ N-ABLE is based on the Sandia Aspen model (Basu and Pryor (1997), Basu et. al. (1996), Barton et. al. (2000)) and employs a new object-oriented architecture for the rapid development of different agent types and communication between different agents on different systems (see Ehlen and Eidson (2003)). While the generation sector could also have been modeled in N-ABLE, it is run remotely as part of an on-going NISAC research effort to develop formal protocols for co-joining different simulations and platforms into wide-area distributed simulations.

In Section 2 we construct the three parts to the N-ABLE model of power generation, distribution, and usage: households; representative commercial and industrial sectors that balance the effect of residential use on total power loads and system prices; and a demand aggregator (Transco) who sells bilateral contracts to its customers and buys electric power from the generation sector. The section rigorously formulates a model of how households evaluate, purchase, and consume power under real-time and uniform pricing contracts. Section 3 describes the distributed two-model simulation and summarizes with a discussion of the primary results. Section 4 concludes.

³ National Infrastructure Simulation and Analysis Center, a collaboration between Sandia National Laboratories and Los Alamos Laboratory funded by the Department of Homeland Security.

⁴ N-ABLE uses the gSOAP C/C++ generator tools (<http://www.cs.fsu.edu/~engelen/soap.html>) while the generation sector uses the Java 1.4 SOAP Implementation (<http://java.sun.com/webservices/>) and Apache Tomcat Server (<http://jakarta.apache.org/tomcat/>).

2 The Models

The N-ABLE model of power distribution and use is composed of H households, representative commercial and industrial sectors, and a single demand aggregator of this usage (Transco). The Java-based generation sector models the industry supply of power to the use sectors. Each is discussed in turn.

2.1 Residential Use (Households)

N-ABLE household agents model the hourly electric power use of real households. Currently, most real households pay a fixed electricity rate regardless of the time of day and therefore use power at the times and levels they desire. With real-time pricing contracts, however, households will likely shift some of their peak-hour power use to low-price hours; for this we need some structure to how households use power and how they will re-schedule usage under RTP contracts.

2.1.1 Hourly Consumption

We formulate a framework of residential power use with sufficient fidelity to characterize households with different power use patterns, different levels of inconvenience to re-allocating power use, different budget constraints (e.g., caused by different income levels), and different sensitivities to external social conditions. To categorize the relative temporal importance of power usage for households, independent of the price paid, each household's total daily *desired* use of electric power is divided into three specific types of usage:

Optional Use - this is power consumption of relatively low consequence; if interrupted, the household does not need to make up for the loss of use. If power becomes expensive, households are expected to reduce or eliminate their use of this power. Examples: lighting, radios, and televisions.

Moveable Use - power consumption of medium consequence and flexible scheduling; if interrupted, its use can be rescheduled to another time. Examples: dishwashers, dryers, and hot-water heaters.

Immoveable Use - power consumption that must be consumed at its scheduled time; if it isn't, critical needs are not met. Immoveable use typically fluctuates according the weather of the particular day, being higher during extreme hot or cold conditions. Examples: food refrigeration in the summer and central heating in the winter.

Each usage type is modeled as a diurnal 1×24 vector of hourly usage, in KWh (see Figure 3 for graph of our distribution of household hourly use). Denoting

$e_j^{h,t}$ as the consumption of electric power of type j by household h at hour t , where $j = \{\textit{optional}, \textit{moveable}, \textit{immoveable}\}$, the desired vectors of optional, moveable, and immoveable usage, $\hat{e}_j^{h,t}$, are

$$\hat{\mathbf{E}}_o^h = [\hat{e}_o^{h,1} \quad \hat{e}_o^{h,2} \quad \dots \quad \hat{e}_o^{h,24}], \quad (1)$$

$$\hat{\mathbf{E}}_m^h = [\hat{e}_m^{h,1} \quad \hat{e}_m^{h,2} \quad \dots \quad \hat{e}_m^{h,24}], \quad (2)$$

and

$$\hat{\mathbf{E}}_i^h = [\hat{e}_i^{h,1} \quad \hat{e}_i^{h,2} \quad \dots \quad \hat{e}_i^{h,24}]. \quad (3)$$

Total hourly power usage $\hat{\mathbf{E}}^h = [\hat{e}^{h,1} \quad \hat{e}^{h,2} \quad \dots \quad \hat{e}^{h,24}] = \hat{\mathbf{E}}_o^h + \hat{\mathbf{E}}_m^h + \hat{\mathbf{E}}_i^h$.

2.1.2 Re-scheduling Consumption

During the course of the day, a household tries to maintain the desired hourly levels of all three types of use. If the household has a uniform price contract, the particular hour of the day is irrelevant and the household can use its desired levels. If, however, the household has a real-time pricing contract and average prices are high relative to its budget for power use, then it may want to re-distribute consumption from high-price to low-price hours of the day. At the start of the day, a household with a real-time price contract evaluates if the desired distribution of consumption can be afforded, given the day's pricing (defining p^t as the price of electric power at hour t) by computing the total cost of the desired consumption, and seeing if this is not greater than the daily electricity budget, I^d :

$$\sum_j^{\{o,m,i\}} \sum_{t=1}^{24} p^t \hat{e}_j^{h,t} \leq I^d. \quad (4)$$

If inequality of Equation 4 also does not hold, the household will first attempt to re-schedule the moveable use to lower-price hours of the day. We use a “greedy” scheduling algorithm⁵ to represent a heuristic human mental planning process: the household finds the most costly amount of movable usage (the amount of movable use power times the price of power at that hour) and moves it to the daytime hour with the lowest price. It then marks both time slots as “busy,” (that is, not available for rescheduling⁶) and recomputes

⁵ For more information on greedy algorithms, see <http://www.nist.gov/dads/HTML/greedyalgo.html>.

⁶ We are modeling how each hour a household can accomplish only so many tasks, so each off-peak hour that gets new movable load is added to only once.

Equation 4 with the new t . If the inequality is not satisfied, it continues the greedy algorithm, addressing the moveable use component that is now the most expensive hour of the day, until either all the moveable power uses have been rescheduled or until the budget condition is met.

2.1.3 *Selecting the Type of Power Contract*

Whether a particular household adopts a real time pricing contract is a complex process dependent on at least four factors: the relative economic advantage of the alternative contracts, the cost of initiating the change (e.g., economic *transaction costs*), the willingness of the household to experiment with the new form of power contract, and the social exposure and acceptance of the contract. For the last factor, a household's willingness to consider a new contract, at least for a subset of households, is likely a function of the current level of adoption in the market place. This adoption, in turn, is a function of information a household gets from the market *and* its social/cultural interactions with other households.

Social networks are modeled explicitly in N-ABLE.⁷ Since a household that is satisfied with its RTP contract will likely socially recommend this contract, N-ABLE increases the probability that any given household will try real time pricing when the number of households that currently have the contract increases. Likewise, since when a household defects from its RTP contract to a uniform contract it is likely to socially network to others its dissatisfaction with the contract (e.g., it was too inconvenient to reschedule usage), a decrease in RTP contracts decreases the probability that a household will try an RTP contract. Furthermore, N-ABLE models how a household can sequentially experiment with an RTP contract, find it personally inconvenient, and switch back permanently to a uniform price contract. So that the simulation starts with a non-zero number of households with RTP prices, a small fraction of household agents are instantiated with RTP contracts. The cost of initiating a change in a contract is modeled on the household side by explicitly imposing a transaction cost; this creates a mild hysteresis in agent choices, thereby reducing vacillation between contract types.

The economic advantage of the contracts is measured directly by the agents. At the end of each month, the households compute whether they have actually saved money under the contract, by comparing their actual expenses under variable pricing to their expected expenses under fixed pricing (which the power utility changes and advertises regularly).

⁷ N-ABLE, to be consistent with mechanisms in economic theory, groups interactions between agents into market-based and non-market-based interactions. Market-based interactions occur between buyers and sellers in a market (for, say, electric power). Non-market interactions occur through N-ABLE social networks.

To capture the rigidity with which some households are willing to make change of any kind, we randomly assign a probability of switching to each household, where a pure experimentalist household has a probability of 1.0 of actively engaging in the above opportunities and a pure passive household a probability of 0.0. In all cases, a household that has tried an RTP contract and defected out of it does not experiment again (this will tend to put a physical bound on the number of steady state RTP contracts in the system). We do, however, include in the model the migration of households in and out of the residential sector: each year two percent of households randomly move out of the sector and are replaced by new households that are willing to experiment with RTP contracts.

2.2 Commercial and Industrial Use

To capture how the commercial and industrial sectors diminish the potential effects of household demand elasticity on system loads and market prices, we also include representative commercial and industrial use sectors, each with a diurnal power use cycle based on data described below. These sectors are invariant with respect to their contracts and their hourly usage of power.

2.3 Demand Aggregator (Transmission and Distribution)

To service the power needs of households, the model includes a demand aggregator that purchases power from generating companies and resells it to each household (and commercial and industrial sectors) through either a uniform or RTP contract. The power demand aggregator offers contracts at prices that allow it to satisfy three objectives: (1) deliver the power that is demanded, (2) maintain the target rate of return from its portfolio of contracts, and (3) create new opportunities for selling excess transmission capacity on open short-term markets.

To model objectives 1 and 2, we mathematically define the triplet $\{p^{h,t}, p^{c,t}, p^{i,t}\}$ as the prices the demand intermediary charges each household and the commercial and industrial sectors, respectively, at hour t , c^t the price it pays for power at time t , d the current day and r the targeted (i.e., regulated) rate of return. The demand aggregator's problem is then to select the set of uniform and RTP prices it charges to households and the quantities (and associated prices) it purchases from generation companies, $\{q^{d,t}, c^{d,t}\}$ such that it maintains regulated requirements for solvency, i.e., its rate of return equals

a regulated fixed rate \bar{r} :

$$r(p^{h,t}, p^{c,t}, p^{i,t}; c^{d,t}, q^{d,t}) = \frac{R - C}{C} = \bar{r}, \quad (5)$$

where

$$R = \sum_{d=1}^{30} \sum_{t=1}^{24} \left(\sum_{h=1}^H p^{h,d,t} e^{h,d,t} + p^{c,d,t} e^{c,d,t} + p^{i,d,t} e^{i,d,t} \right) \quad (6)$$

$$C = \sum_{d=1}^{30} \sum_{t=1}^{24} c^{d,t} q^{d,t} \quad (7)$$

$$q^t = \left(\sum_{h=1}^H e^{h,t} \right) + e^{c,t} + e^{i,t}, \quad t = 1, 2, \dots, 24. \quad (8)$$

Objective 3 is achieved by maximizing its excess peak-hour transmission capacity that can be sold in short-run markets. This can be achieved by selling RTP contracts to customers that switch their peak-hour usage to off-peak hours.

To distribute power from aggregator to user, N-ABLE contains a detailed distribution network. Thus infrastructure is composed of *sinks* into which the commodity is poured, *spigots* from which the commodity is dispensed, and the network representation. This highly flexible system is designed to model real-world systems (power, water, gas, data) where suppliers, customers, transmission, and network topology change over time.

Since we are essentially modeling the “last mile” of distribution, our N-ABLE infrastructure is composed of one sink for the demand aggregator, a simple zero-sum network (flow out equals flow in), and thousands of spigots that are being attached and removed as power users purchase new contracts and switch contracts.⁸

2.4 Generation

We model the generation sector with a typical “hockey stick” representation of electric power supply (Figure 1) that has two distinct market regimes: a

⁸ The N-ABLE infrastructure includes an interrupt detector, which determines whether all “pulls” by the spigots can be met by the capacity of each sink; if not, then the detector rations the supply to the spigots. Different real-world networks can be represented by different interrupt detector functions.

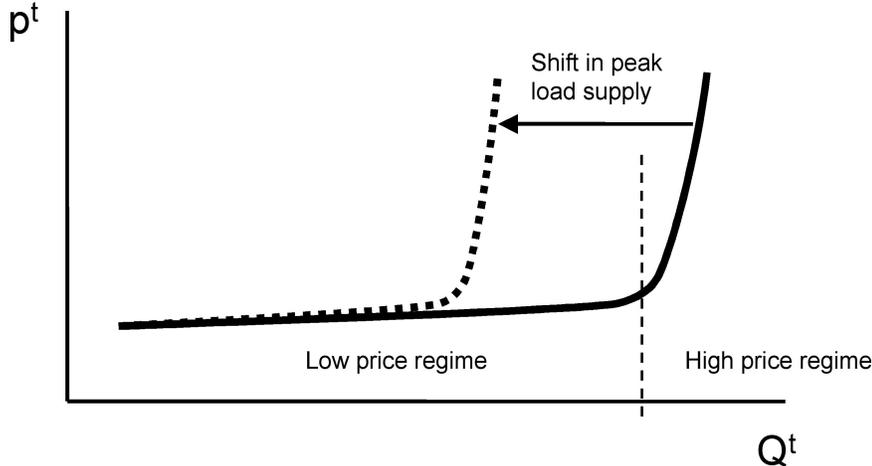


Fig. 1. Representative Generation Supply Curve

low price regime where additional demand can be met with small increases in price, and a high price regime where prices rise dramatically with increases in demand. Since by design our long-run demand will be relatively constant, we model random price spikes as changes in the supply conditions in the generation side of the market, specifically, lateral shifts in the vertical part of the supply curve (as shown by the dotted line). As mentioned in the introduction, these shifts can also represent withheld base-load generation.

Mathematically, the two distinct price regimes are represented as the sum of linear and non-linear (quadratic) terms, using Equation 9. This Heaviside step function⁹ removes the non-linear term for quantities less than the system critical quantity, Q_c . At quantities above the system critical quantity, the linear term makes a contribution, but the non-linear term dominates the equation, leading to dramatic price spikes.

$$P^h = P_{base} + K_{linear}Q^h + K_{nonlinear}(Q^h - Q_c)^2\theta(Q^h - Q_c). \quad (9)$$

This equation can be tuned to represent supply pricing of interest by varying P_{base} , K_{linear} , $K_{nonlinear}$, and Q_c . To ensure the overall representational accuracy of this model, we tuned these four parameters over a demand region of interest against 1999 regional wholesale price information available from Energy Information Administration (2000) and University of California Energy Institute (2003). Under normal conditions, prices in RTP contracts fluctuate within the lower, flatter portion of the curve. At random intervals power supply is reduced such that RTP contract high prices can spike significantly.

⁹ See <http://mathworld.wolfram.com/HeavisideStepFunction.html>.

Table 1
Generation Pricing

Parameter	Values
Off-peak/peak prices	\$21.65 / \$49.90
Off-Peak/peak demand	24.8 MWh / 48.4 MWh
P_{base}	-\$8.04
K_{linear}	1.20 \$/MWh
$K_{nonlinear}$	1.75 \$/MWh ²
Q_c	54.7 MWh

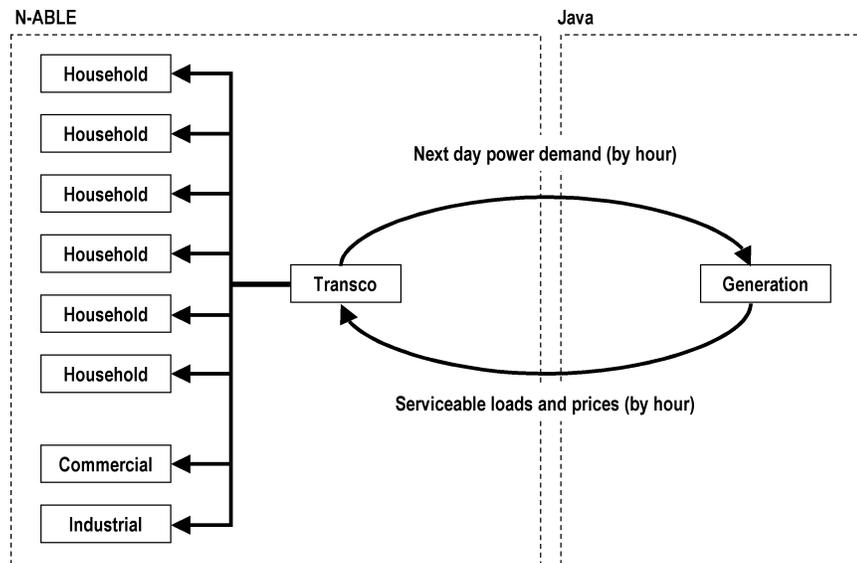


Fig. 2. Daily Data Exchange Between N-ABLE and External Generation and Transmission Models

3 Simulations

Analysis was conducted using a distributed simulation composed of the N-ABLE model and Java-based generation sector. The combined simulation leverages the strengths of domain-specific specialized models in exchange for some loss in speed of execution. An explicit set of basic but extensible communications was established between the two (Figure 2).

3.1 General Mechanics

There are three recurring decision intervals in the simulations:

Monthly decision interval - At the beginning of each month households evaluate their spending on electric power; if not satisfied, then they re-evaluate their current contract. If the household has a uniform contract and hasn't had an RTP contract before, it may (probabilistically) experiment and try one. If the household has an RTP contract and that contract has been either too expensive compared with current uniform rates, too inconvenient, or both, the household switches to a uniform contract (and never returns to RTP). The households also pay their end-of-month utility bills. The power demand aggregator evaluates its solvency condition and if necessary, revises the pricing of its contracts with households.

Daily decision interval - At the beginning of each day, the power demand aggregator sends to the generation side its forecast for the day's hourly power needs, and then receives back the day's serviceable loads and prices, which it then adjusts and sends on RTP households. Household agents with RTP contracts then determine whether and how to adjust their day's usage.

Hourly action interval - Each hour, household agents consume electric power according to their desired levels and log the use for payment at the end of the month.

To create households with different consumption patterns, random components were added to a baseline vector of average power use. Letting \bar{e}_j^t be the average level of power used at time t and ϵ^t be uniformly distributed around zero ($\epsilon^t \sim N(0, \sigma^2)$), each agents desired power usage (by type) is modeled as

$$\hat{\mathbf{E}}_j^h = [(\bar{e}_j^1 \times \epsilon^1) \quad (\bar{e}_j^2 \times \epsilon^2) \quad \dots \quad (\bar{e}_j^{24} \times \epsilon^{24})]. \quad (10)$$

3.2 Industry Data

To calibrate our hourly usage profiles with representative data, we applied the hourly distribution patterns listed in Brown and Koomey (2002), but scaled down by a factor of 1000 (from GW to MW). The residential data, illustrated in Figure 3, groups usage by machine (e.g., Air Conditioning); we used this figure to first classify each group as either optional, movable, or immovable use, and then estimate each as a percentage of total use. Table 2 lists the resulting groups and estimated percentages of total.

Figures 4 and 5 were used to create hourly load distributions that, along with the hourly residential loads, constitutes total load experienced by the local power utility.

Finally, Table 3 lists the variables and ranges of values used in the sets of simulations.

Table 2
 Estimating Optional, Immovable, and Movable Power Usage

Type	Equipment	% Total
Immovable Use	Air conditioning	70.0 %
	Refrigerator	
	Cooking	
	Miscellaneous	
Movable Use	Washer, Dryer	25.0%
	Dishwasher	
	Domestic Hot Water	
Optional Use	Television	5.0%

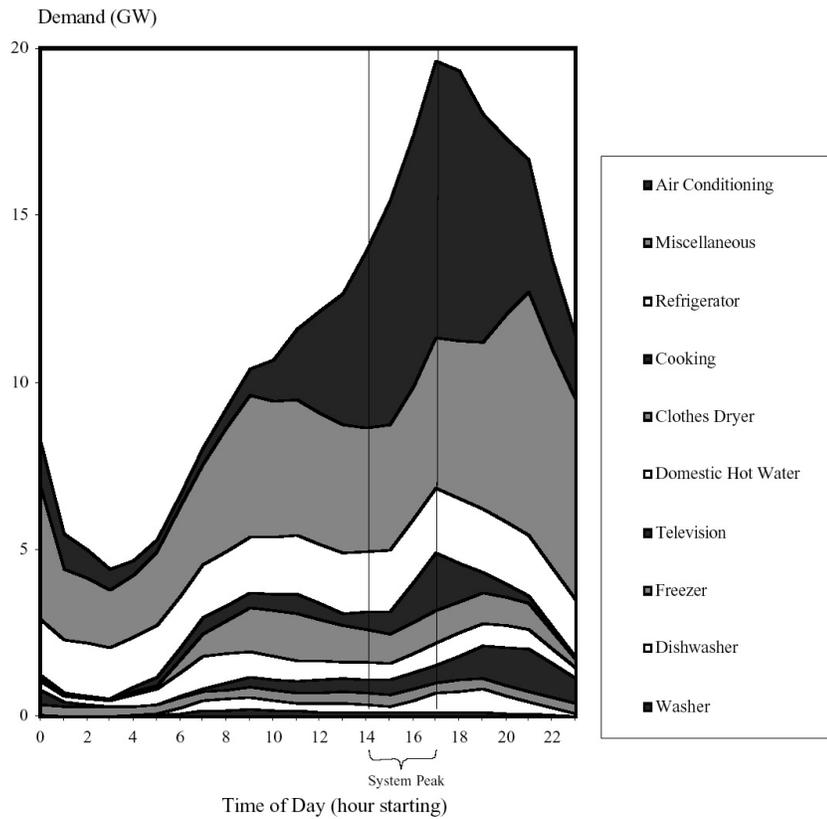


Fig. 3. Household Hourly Use Profile (from Brown and Koomey (2002))

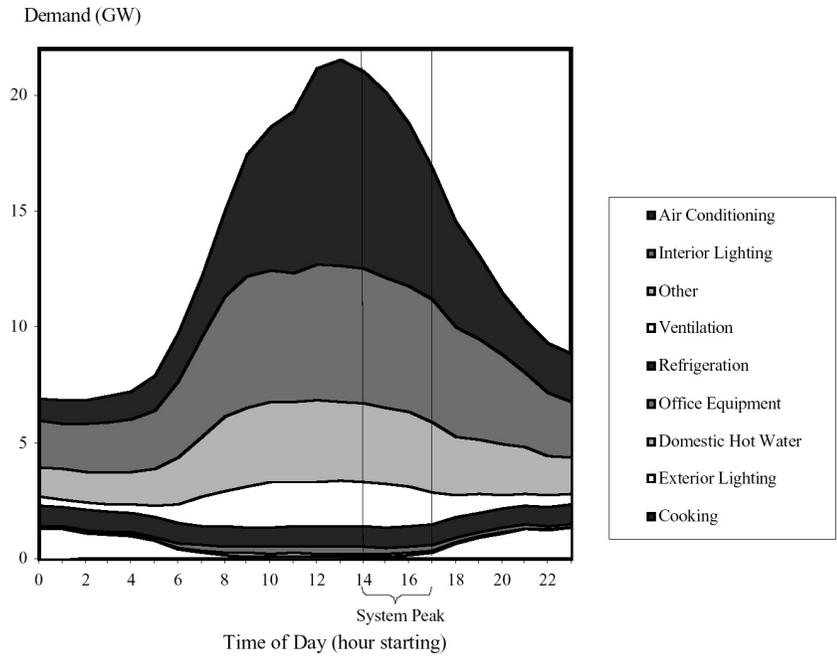


Fig. 4. Commercial Hourly Use Profile (from Brown and Koomey (2002))

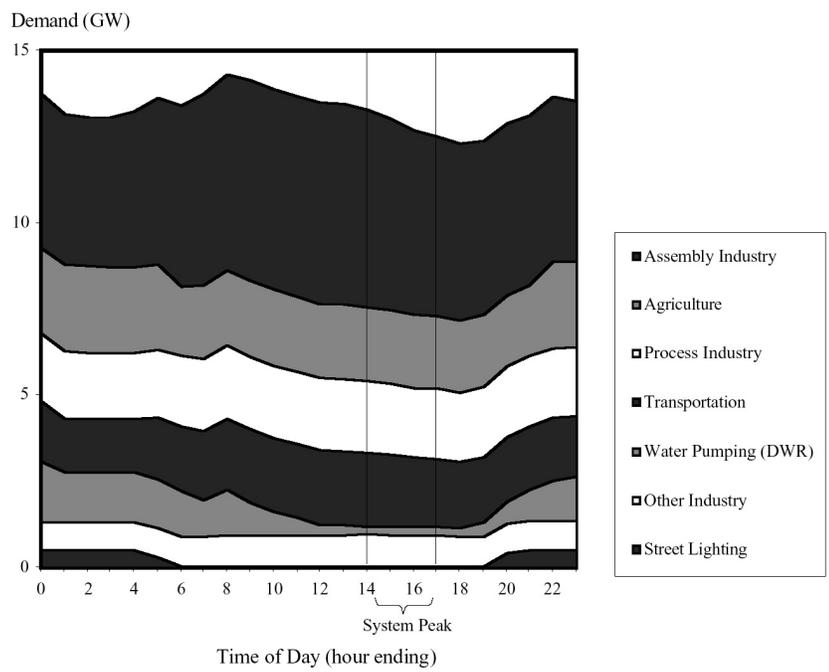


Fig. 5. Industrial Hourly Use Profile (from Brown and Koomey (2002))

Table 4 lists the four sets of simulations that were conducted; each was composed of 10,000 residential sector agents (representing households), one local power utility, one commercial/industrial use sector, and one generation sector.

Table 3
Power Provision and Usage Parameters

Agent	Parameter Settings
Power Utility	Number of agents: 1 Initial advertised price (per KWh): [\$0.01, \$0.10] Uniform price change increment (%): 5% Regulated rate of return (%): 5%
Residential	Number of agents: 10,000 Daily consumption: [25.3 KWh, 31.0 KWh] Variation in average hourly consumption: +/- 25 % Monthly budget: [\$30.0,\$50.0] Cost of switching consumption: [0.00, 0.00001] Contract transaction cost: [\$50, \$100] Probability of experimenting with RTP: [0.0,1.0]
Commercial	Number of agents: 1 Daily consumption: 328.3 MWh
Industrial	Number of agents: 1 Daily consumption: 319.6 MWh

Table 4
Simulation Sets

Sim. Set	Residential Contract
Set #1	Uniform price only
Set #2	RTP price only
Set #3	Uniform and RTP - no price spikes
Set #4	Uniform and RTP - with price spikes

3.3 Summary of Results

When the power distributor offers only uniform price contracts, it can maintain a fairly stable price for power. Price shocks are generally effectively absorbed by incremental increases in later uniform prices. Since households achieve no personal cost savings by shifting power, their actual hourly usage follows their

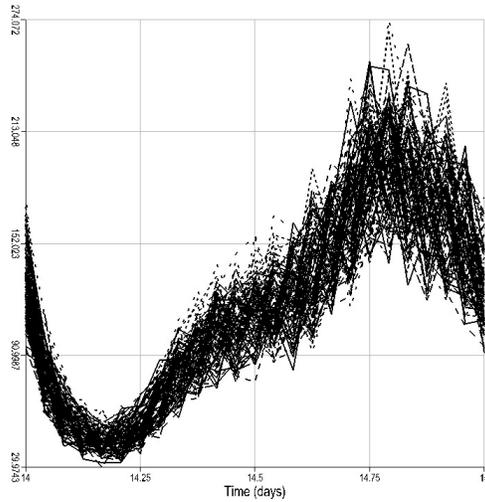


Fig. 6. Residential Hourly Usage: Uniform Price Contracts

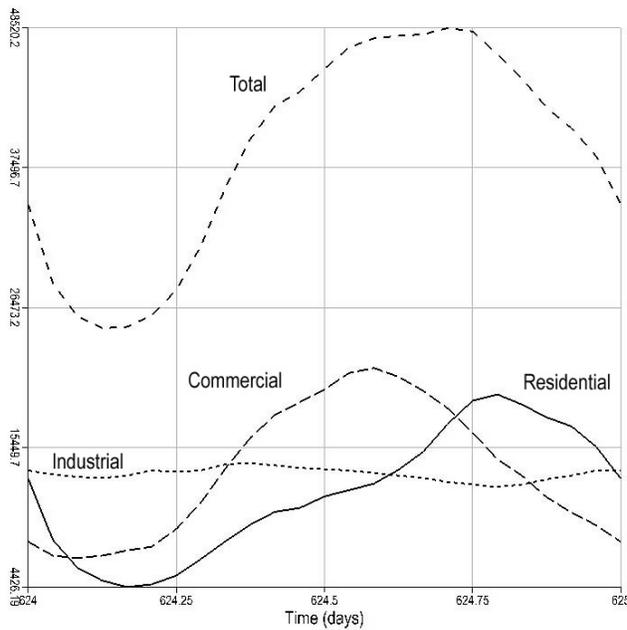


Fig. 7. Hourly Usage: Residential, Commercial, and Industrial Usages

desired profiles, shown in Figure 6. The contribution that this residential usage makes to overall system usage (which includes the Commercial and Industrial sectors) is shown in Figure 7.

When the power distributor offers only RTP contracts, those households that have relatively low budgets for monthly power usage shift their usage from peak hours to off peak hours. Figure 8 illustrates how the set of 10,000 agents shift their desired usage (in the left panel) to a usage that reduces their usage of peak-hour power (in the right panel). The extent of this load shifting is

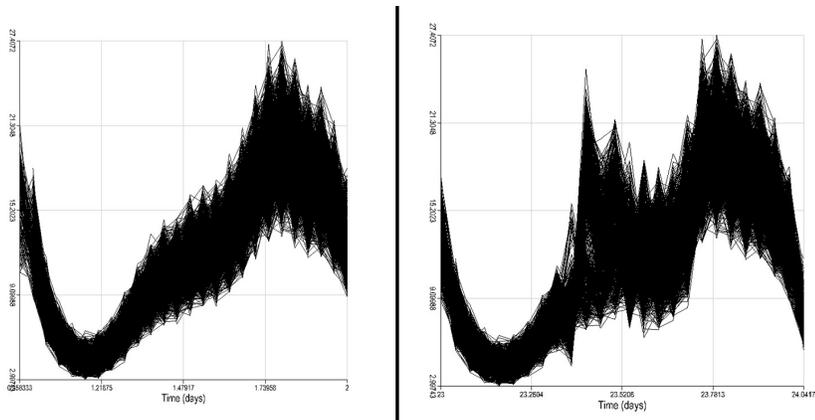


Fig. 8. Residential Hourly Usage: Uniform Price-Only (Left) and RTP-Only Contracts (Right)

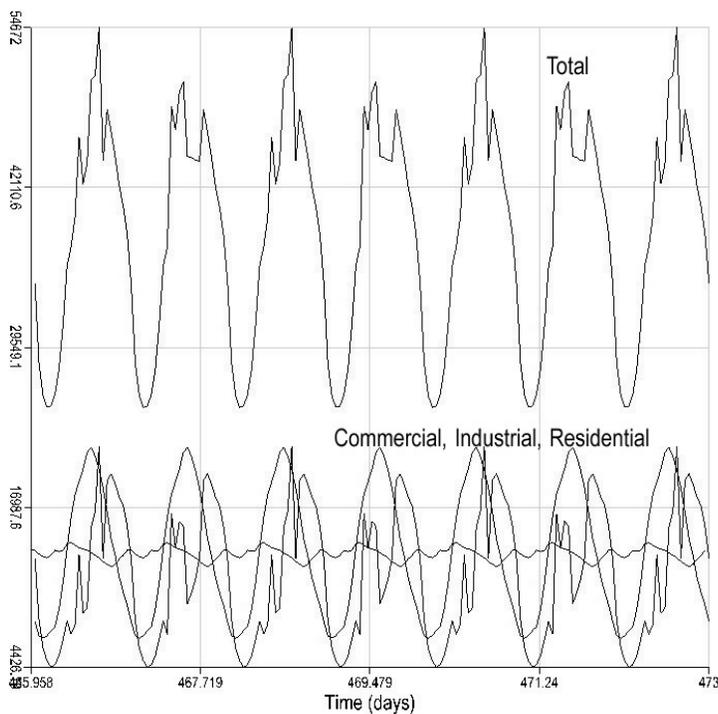


Fig. 9. Demand Aggregator’s Hourly Loads: RTP-Only

a function of (1) households’ monthly budgets for power (i.e., their personal urgency to reschedule usage), (2) the fraction of total usage that they determine to be movable, and how aggressively the distributor increases its RTP peak-hour prices from the peak-hour prices *it* pays for power.

Despite the conservative assumptions used in formulating the model (the fractional contribution of the residential sector to the overall power market, voluntary and rational participation in the RTP program, differentiation between moveable and immovable household power use, and economic and demographic

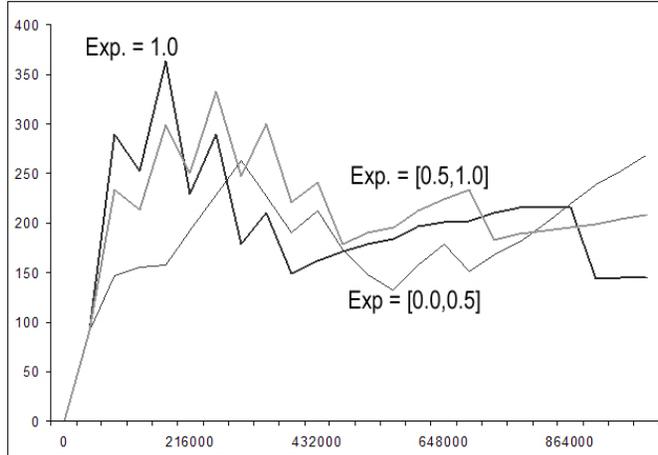


Fig. 10. Number of RTP Contracts Over Time: Various Experimenting

variance in households), RTP does have a substantial system-wide effect. In aggregate, the RTP-only contracts shift the distributor's total system loads away from peak hours, as illustrated by the upper curve in Figure 9; the power demand aggregator's peak-hour loads reduce by 25 percent and peak hour prices by 15 percent.

The system-wide effects of residential load rescheduling are in fact so significant that cyclic shifts in system peak hours are observed. This phenomenon occurs as households shift moveable power usage to the lowest cost hour, and since all households share this information, this hour becomes the new peak hour, causing the power demand aggregator to raise the rate for this hour. In response the households shift power use to the new lowest cost hour, initiating another system peak and subsequent price correction from the demand aggregator. In two or three days, the households move their peak usage back to the first lowest cost hour. Clearly this price circularity could be ameliorated if the demand aggregator adjusts the RTP contract prices it charges across its customer base to prevent such coordinated load shifting.

The most interesting results occur when the power demand aggregator offers both types of contracts. As illustrated in Figure 10, each month a fraction of uniform-contract customers experiment and try an RTP contract. Over time, a fraction of households will stay with RTP; they will be the fraction that either (1) find it economical to save money by re-scheduling loads to off-peak hours, (2) have sufficient income that re-scheduling load is unnecessary, or (3) are passive and are likely not to make a move of any kind; the other fraction will likely opt out of RTP and stay with uniform thereafter.

This rate of acceptance and defection is a function of the willingness of households to experiment. The top line shows the number of RTP contracts when every household agent has an experiment value of 1.0; mass acceptance of RTP contracts is fast and high, but so is defection out of RTP contracts. As the

values of experimentation decline, to a range of $[0.0, 0.5]$, acceptance is much slower but does not include significant defection.

4 Summary and Conclusions

There are three main findings of these simulations. First, a power demand aggregator increases profits by selling a significant number of real-time pricing contracts to customers that actively reschedule their use of electric power during peak load hours. It decreases its average per-MWhr cost of power as its load moves from peak to off-peak hours, and it increases its opportunities for selling excess transmission capacity during peak-price hours.

Second, a distributor can realize supra-normal short-term profits if it is an aggressive first-marketer of RTP contracts. By rapidly converting its residential sector toward shifting load to off-peak hours, it can have excess transmission capacity that is far greater than its transmission competitors.

Finally, a distributor must be cautious in establishing a RTP contractual structure in order to avoid any rapid, large-scale switching from RTP to uniform contracts, such as after a series of large price spikes. If, for example, a distributor were to pass to its RTP customers a price spike large enough to cause switching en masse to uniform price contracts, thereby rapidly increasing the distributor's load during peak hours, the distributor would potentially have to purchase peak-price power via short-term, more expensive mechanisms.

Historically, large-scale defections from RTP have occurred, as in the case of retail customers in San Diego Gas and Electric's (SDGE) service territory in Southern California during the summer of 2000. Being the first Investor-Owned Utility (IOU) to successfully meet obligations and regulatory restrictions specified with the Electric Utility Industry Restructuring Act (AB 1890) and its accompanying rules, SDGE won the right to pass along to all its' customers the real-time market price of power on each monthly bill. The summer of 2000 saw a substantial increase in price over the previous (uniform) structure. Customer outrage at this event - across all customer types - led not to a change in demand behavior, but rather to action on the part of both the state legislature and the Public Utilities Commission to lock in rate ceilings of 6.5 cents per kilowatt-hour; and to credit customers for charges above the rate cap.

Any RTP contractual structure introduced might, therefore, for the sake of the distributor, have to include a minimum time window within the contractual obligation, with penalties for early termination, similar to those included in cellular phone contracts. This would reduce the risk to the distributor of

rapid change in expected peak-hour demand, with the only avenues of recourse being (1) meeting the increased demand with short-term, high-price power contracts, providing an ever-increasing negative feedback on the price paid by RTP customers and on the willingness of RTP customers to maintain their contracts, or (2) interruption of non-firm and/or firm demand in place of meeting this unexpected demand.

In general, the N-ABLE model of residential power consumption is rich enough and flexible enough to model a range of residential power contracts and associated parameters. Further work is planned, therefore, to study various ways to impose these contractual limits, as well as more complex power demand aggregator pricing strategies, such as the optimized pricing of residential RTP hourly premiums above power costs. We also plan on extending our analysis to multiple power region scenarios to better understand pricing strategies between power demand aggregators that compete to sell excess transmission capacity.

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