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Monte Carlo Analysis of Real-Time Electricity Pricing for Industrial Loads

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Abstract

Maintaining a competitive industrial business demands close cost control. Free market wholesale electricity suppliers offer a variety of purchase agreements. Suppliers now offer real-time pricing to all customer classes with the promise of potential savings. Real-time price tariffs mirror the dynamic nature of the wholesale electricity market. This market exhibits high price volatility due to constantly changing demand and lack of large-scale electricity storage technology. Businesses may benefit from these market changes depending on their load characteristics. This paper uses Monte Carlo analysis to determine the potential economic benefit of adopting a real-time price rate under different load parameters. Sections of this paper introduce load models for electric demand, define a benefit model, develop an expression for equivalent break-even fixed rates, examine parametric variation, and record simulation results. Simulations show that businesses with a high load factor have a greater probability of profiting from real-time price tariffs without adopting any load control strategy. Businesses with low load factors require higher equivalent break-even rates to benefit from real-time price tariffs.

Introduction

A competitive industrial business must pay attention to all production costs and take advantage of all process improvements that provide potential savings. Free market electricity increased the number of energy suppliers and created opportunities to reduce electricity costs. These suppliers offer a wide variety of service agreements that may reduce customer costs when compared to fixed rate tariffs, but customers must assume load curtailment risk and high price volatility (Borenstein, 2006).

Electricity price control is especially important in high consumption industry sub-sectors. Federal government statistics show that the top five sub-sector electricity consumers are chemicals, primary metals, food, paper and transportation equipment (Energy Information Administration, 2009). These sub-sectors can realize significant savings by studying consumption patterns and alternative tariffs.

Suppliers now market to all customer classes a real-time price (RTP) tariff as a cost saving alternative to the fixed rate tariff (Power Smart Pricing, 2008). Over 70 U.S. based utilities offer RTP tariffs on a permanent or pilot basis to various customer classes (Barbose et al, 2004). Programs exist in every region of the country and have varying levels of acceptance. The programs help mitigate suppliers' market power and reduce price volatility by sending economic signals to customers that allow them to modify their power demand based on market price.

The RTP tariff gives customers access to the daily price variations of the wholesale electricity market. These prices reflect the hourly supply and demand conditions on the grid and are highly volatile. Although this tariff may have savings potential, customers must study their load pattern and compare it to the RTP before adopting the tariff. Load patterns that peak coincident to RTP rates introduce higher electricity costs, especially for sustained load peaks.

Customers who require steam for industrial processes can co-generate electricity to control their peak demands and reduce purchased electricity costs when RTP rates spike (Sarimveis et al., 2003; Coffy and Kutrowski, 2005). In general, industrial load control would require additional investment in energy management systems and customer-owned generators to reduce consumption during times of high prices. Recovering the cost of this equipment depends on the potential savings, if any, realized from adopting the RTP tariff. Shifting or curtailing industrial operations is another method of load control but maybe too costly or impractical to implement.

Previous researchers produced deterministic dynamic models of industrial customer types using linear and non-linear programming to test the impact of RTP tariffs (David and Lee, 1989). The models generate optimal operating schedules for plant production under an RTP with production constraints. These theoretical models are for evaluating supply and demand interactions, and have value in industrial site planning and process expansion. Hughes and Bailey developed a scheduling methodology using discounted cash flow modeling for optimally allocating co-generating resources in a nylon plant using RTP information (Hughes and Bailey, 2004). In this work, a Monte Carlo simulation evaluated a number of fuel cost and electricity price scenarios to aid in the decision process and risk analysis of optimal co-generator schedules.

This paper examines demand functions to determine what factors influence RTP tariff savings by introducing a benefits index to calculate savings potential. The nominal values of the demand functions derive from analysis of actual plant electricity consumption data. The analysis uses a power demand measure, *load factor*, to characterize industrial load types. The analysis also compares the potential benefits of adopting the RTP tariff to load factors with high and low values. The analysis assumes industrial customers purchase no additional load control equipment.

Electrical Load Representation

One metric for classifying industrial electric load patterns is load factor (Turner, 2001). Load factor compares average power demand to peak power demand for a defined period such as a month or year. Equation (1) defines load factor mathematically. In this equation, E_{total} is the

$$LF = \frac{E_{total}}{P_{peak} N} \qquad (1)$$

total period electric energy usage in kilowatt-hours, P_{peak} is the maximum period power demand in kilowatts during the period, and N is the period length in hours. Customers with high load factors present a nearly constant power demand over time to suppliers while customers with a low load factor have more cyclic power demand patterns. Low load factor industrial operations exhibit cyclic electricity consumption due to daily production changes and shift operations. Industrial customers that operate at full capacity continuously have higher load factors.

Electric demand meters totalize energy consumption over periods varying from five minutes to one hour. These interval values provide industrial customers with power demand information and energy consumption data. Simple calculations convert shorter interval data into equivalent hourly values. Graphing demand meter data produces time series plots of consumer electricity consumption. A Fast Fourier Transform (FFT) decomposition of power demand time series values identifies significant cyclic load components that can be modeled mathematically using sinusoidal terms. The FFT decomposition provides amplitude, frequency and phase parameters for the load model (Cohen, 1995). Random load variations occur in industrial loads also. Stochastic phase and amplitude parameters represent this part of customer load. The sum of the periodic and stochastic load components gives the total customer power demand function.

Equations (2) and (3) simulate high and low load factor industrial loads respectively. These demand functions generate times series load data normalized to peak power demand.

$$d_H(nT_m) = a_{1H}\sin(2\pi f_1 nT_m) + a_{2H}\sin(2\pi f_2 nT_m + \phi_{2H} + \varepsilon_{\phi n}) + d_{baseH} + \varepsilon_{bn} \qquad (2)$$

$$d_L(nT_m) = -a_{1L} d_{base}\sin(2\pi f_1 nT_m + \phi_{1L}) + a_2 d_{base}\sin(2\pi f_2 nT_m + \phi_{2L} + \varepsilon_{\phi n}) + d_{baseL} + \varepsilon_{bn} \qquad (3)$$

These equations represent industrial operations that exhibit daily periodic changes. They include cycles for shift work changes reflecting three eight hour work periods. The variable, T_m, represents the demand meter totalizing period and n is the period index over the total study interval N. The other parameters are:

f_1 = daily frequency = $1/T_1$, T_1 in hours,

f_2 = shift frequency = $1/T_2$, T_2 in hours,

a_{1H}, a_{2H} = daily and shift component amplitudes for high load factor,

a_{1L}, a_{2L} = daily and shift component amplitudes for low load factor,

ϕ_{2H} = phase delay of shift load component for high load factor,

ϕ_{1L}, ϕ_{2L} = phase delay of daily and shift load components for low load factor,

d_{baseH}, d_{baseL} = average power demands for high and low load factors,

ε_{bn} = stochastic average load component,

$\varepsilon_{\phi n}$ = stochastic phase delay component.

Figure 1. Phase Relationship between Demand and RTP.

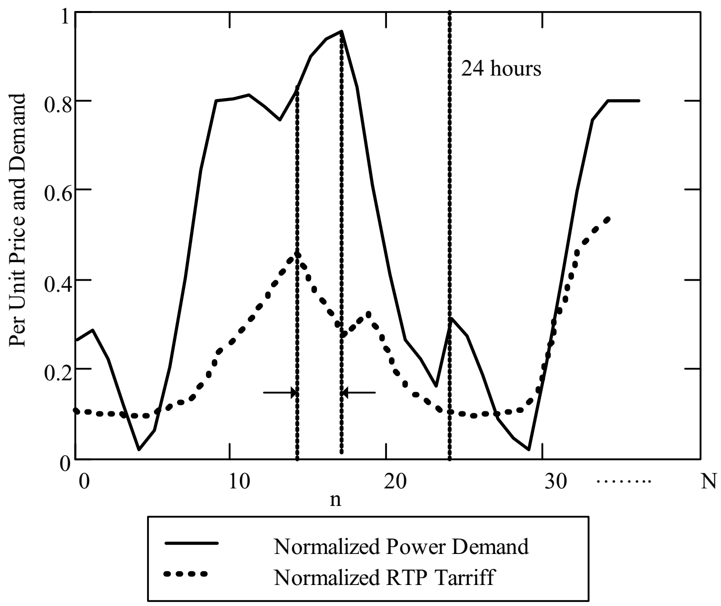


Figure 1 shows the phase delay relationship between the price and load. Phase delay is the angular difference between the real-time price daily peak and load series peak with price as reference. These parameters relate the temporal difference between the two time series. The equations represent random changes in operations with two stochastic variables: one for power demand and another for phase delay. Using load models based on actual consumption data allows energy managers to correlate operation parameters such a work start times to the price series and examine the impact of parameter changes quantitatively.

Electricity Cost And Benefit Calculation

Suppliers provide real-time price information to customers at regular intervals ranging from five minutes to one hour. Some markets publish day-ahead forecasts to help customers manage their loads and reduce costs. These prices reflect the supply/demand relationship of the wholesale electricity markets. The RTP demonstrates high volatility over a daily cycle reflecting the temporal nature of power demand. Weekly and seasonal price cycles appear in long-term time series, reflecting the changes in electric demand due to reduced weekend activity and building indoor environmental control.

Fixed rate tariffs remain constant over defined contract periods. Fixed rate tariffs account for utility fuel costs and capital investment in their systems, and are based on average customer consumption. Fixed rate tariffs include cross-subsidies between customer classes such as industrial, commercial, and residential (Borenstein, 2006).

Most industrial tariffs charge for both electric energy and power demand. Demand charges help suppliers recover costs associated with peak power generation, transmission, and delivery. Electric system owners must construct facilities to handle peaks that may occur for only a single hour annually. The demand charge penalizes customers with lower load factors since their peak power demand is large relative to their total consumption over a billing cycle. The following analysis assumes the same peak demand charges occur for both RTP and fixed customer tariffs.

Dividing the components of the real-time price series, p_n and the fixed rate, p_f, by the maximum RTP price during an interval gives a normalized price sequence, pn_n and normalized fixed rate, pn_f. Equations (4) and (5) compute normalized customer cost for a fixed rate tariff over the interval [0, N] using normalized power demands from (1) and (2). The formulas assume a one hour metering interval, T_m=1. The variables FEC_H and FEC_L are the fixed rate electricity cost indexes for high and low load factor time series respectively.

$$FEC_H = pn_f \sum_{n=0}^{N} d_H(n) \tag{4}$$

$$FEC_L = pn_f \sum_{n=0}^{N} d_L(n) \tag{5}$$

Equations (6) and (7) compute normalized costs for RTP tariffs with REC_H and REC_L representing the customer electricity cost index for high and low load factor consumption patterns.

$$REC_H = \sum_{n=0}^{N} pn_n d_H(n) \tag{6}$$

$$REC_L = \sum_{n=0}^{N} pn_n d_L(n) \tag{7}$$

A benefit index quantifies potential industrial customer savings from adopting a RTP tariff. The indices shown in equations (8) and (9) are the differences between the fixed and RTP costs for both high and low load factor power demand patterns.

$$B_H = pn_f \sum_{n=0}^{N} d_H(n) - \sum_{n=0}^{N} pn_n d_H(n) \tag{8}$$

$$B_L = pn_f \sum_{n=0}^{N} d_L(n) - \sum_{n=0}^{N} pn_n d_L(n) \tag{9}$$

When the index, B, is zero, adopting the RTP tariff produces no additional benefits over a fixed rate. If B is negative, then electricity costs under the RTP tariff are larger than the fixed rate. Adopting the RTP rate is not cost effective for negative values of the benefits index. If B is positive, then the cost of adopting the RTP rate structure is less than the cost of the fixed rate, so a customer would realize savings by switching to the RTP tariff.

Setting the benefit equations to zero finds the break-even normalized fixed rate for adopting a RTP tariff with a given load factor, pn_{f0}. The RTP sequence can be written as the sum of the average RTP over N, pn_{ave}, and the series residuals, pn_{rn}. Setting the benefits equation to zero and replacing the RTP series with the above sum gives:

$$pn_{f0}\sum_{n=0}^{N} d(n) = pn_{ave}\sum_{n=0}^{N} d(n) + \sum_{n=0}^{N} pn_{rn} d(n)$$

Solving this equation for pn_{f0} gives the break-even normalized fixed rate for any load pattern and price time series.

$$pn_{f0} = pn_{ave} + \frac{\sum_{n=0}^{N} pn_{rn} d(n)}{\sum_{n=0}^{N} d(n)} \qquad (10)$$

The second term in (10) quantifies the variation in cost due to price changes about the mean. It accounts for the correlation between the price changes about the series mean and power demand series. Highly correlated prices and demands increase the magnitude of this term. Large demand swings also increase it.

Monte Carlo Experimental Design

Monte Carlo simulation is a tool for analyzing systems with parameter variation or incomplete knowledge of data. This type of analysis is one way to quantify uncertainty in data and model parameters. Monte Carlo simulation results in a probability distribution that describes how uncertainty propagates through a system. Statistical analysis of the resulting distribution describes system performance (Wittwer, 2004).

Four statistical experiments examine the impact of load and price parameter variations on customer benefit functions, equations (7) and (8), for differing load factor demand patterns. Two statistical experiments analyze the impact of demand parameter variations on the break-even fixed rate given by (10). Table 1 shows the fixed and random variables for the six experiments. The first four experiments study how variation of average power demand, phase delay, and fixed rate prices impact customer benefits when compared to a real-time price tariff. The remaining two experiments examine how load function parameter variations affect the break-even fixed rate. The first four experiments capture load factor effects by comparing the benefits from the two different demand patterns.

For each experiment, N=648 hours. This number represents 27 consecutive days of hourly usage. Each experiment computes results for 5000 iterations of the benefit indices using the fixed and random variables from Table 1. The experiments use historical real-time price data (Ameren, 2009) normalized to the peak hourly price over a 27-day interval in August, 2007 for these computations. All experiments use this RTP time series.

The Ameren site archives an hourly RTP time series beginning on December 28, 2006 and running to the present. This data derives from the Midwest regional wholesale electricity market. Similar data is available for every region of the U.S. from the Federal Energy Regulatory Commission Website (Federal Energy Regulatory Commission, 2009). The Ameren site also posts day-ahead prices that are next day RTP forecasts. The site updates the day-ahead prices with RTP prices at 4:30 pm CST each day. RTP tariff customers use the day-ahead prices as indicators of the actual RTP to adjust their load profile.

Table 2 lists the parameter values and probability distributions for the power demand functions used in the first four experiments. This analysis assumes a uniform probability distribution for

Table 1. Customer Benefits Experiment Construction

Experiment	High Load Factor Demand Function Parameters		Low Load Factor Demand Function Parameters	
	Fixed	Random	Fixed	Random
1			$a_1, a_2, f_1, f_2, \phi_1, \phi_2, pn_n$	d_{baseL}, pn_f
2			a_1, a_2, f_1, f_2, pn_n	$\phi_1, \phi_2, d_{baseL}, pn_f$
3	$a_1, a_2, f_1, f_2, \phi_1, pn_n$	d_{baseH}, pn_f		
4	a_1, a_2, f_1, f_2, pn_n	ϕ_1, d_{baseH}, pn_f		
5	f_1, f_2, pn_n	$a_1, a_2, \phi_1, d_{baseH}$		
6			f_1, f_2, pn_n	$a_1, a_2, \phi_1, \phi_2, d_{baseL}$

phase delay, base power demand, and fixed tariff parameters. A normal distribution represents the random phase delay and base load variations in the power demand functions. The analysis considers a daily power demand period of 24 hours and a production shift period of eight hours. Figure 2 shows weekly high and low load factor time series computed using nominal parameter values of $\phi_{2H}=\phi_{2L}=\pi/4$, $\phi_{1L}=\pi/3$ $d_{baseH}=0.8$ for high load factor and $d_{baseL}=0.5$ for low load factor. The high load factor demand model is based on a case study of a blow-molding factory running continuously at full capacity producing plastic soda bottles. The low load factor demand model is based on a case study of a soda bottling facility operating a 5-day week and a single shift.

For price experiments 5 and 6, a_1 and a_2 are uniformly distributed normalized values. Table 3 lists the distributions used in experiments 5 and 6 for the parameters that differ from the benefits experiments. The simulation computes 5000 iterations of the break-even fixed rate, pn_{f0}, for both load factor cases.

Simulation Results And Discussion

The Monte Carlo simulation results show how load and fixed rate variations impact potential customer savings from adopting a RTP tariff. These simulations assume that an industrial customer takes no other actions to control peak load or overall electricity usage. Experiment 1 simulates customer benefits using the low load factor power demand function with uniformly distributed average power demand factors and fixed electricity rates. The daily and shift phase delay parameters remain constant at $\phi_{1L}=\pi/3$ and $\phi_{2L}=3\pi/4$. Experiment 2 computes customer benefits for three uniformly distributed variables: average power demand, electricity rates, and phase delay. Experiments 3 and 4 replicate Experiments 1 and 2 using the high load factor power demand equation. Experiments 3 and 4 only include a shift phase delay parameter, $\phi_{2H}=3\pi/4$.

Table 2. Parameter Values and Probability Distributions for Load Functions.

Parameter	High Load Factor (H)	Low Load Factor (L)
a_1	0.05	0.80
a_2	0.08	0.30
ϕ_1 (rad)	N/A	$P_U(\pi/12,\pi)$
ϕ_2 (rad)	$P_U(3\pi/12,3\pi)$	$P_U(3\pi/12,3\pi)$
d_{base}	$P_U(0.3,0.6)$	$P_U(0.3,0.6)$
T_1 (hrs)	24.00	24.00
T_2 (hrs)	8.00	8.00
f_1 rad/hr	$\pi/12$	$\pi/12$
f_2 rad/hr	$\pi/4$	$\pi/4$
$\varepsilon_{\phi n}$	P_N(M=1, SD=2.5)	P_N(M=1, SD=2.5)
ε_{bn}	P_N(M=0.01,SD=0.025)	P_N(M=0.01,SD=0.025)
pn_f	$P_U(0.10,0.80)$	$P_U(0.10,0.80)$

Figure 2. Power Demand Time Series Showing Weekly Patterns of High and Low Load Factor Industrial Operations.

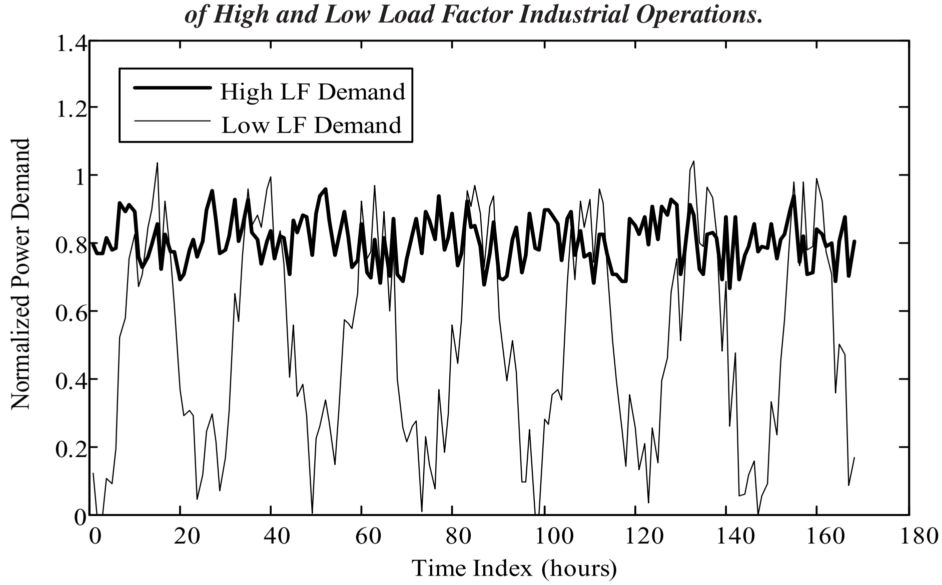


Table 3. Parameter Probability Distributions for Price Experiments.

Parameter	High Load Factor (H)	Low Load Factor (L)
a_1	$P_U(0.05, 0.01)$	$P_U(0.80, 0.10)$
a_2	$P_U(0.08, 0.01$	$P_U(0.80, 0.10)$

Table 4. Monte Carlo Simulation Results-Benefit Index.

Experiment	Load Factor		Benefits Index	
	Mean	Variance	Mean	Variance
1. Low load factor, random fixed rate and average load parameter.	0.481	$2.0\ 10^{-6}$	24.680	3927
2. Low load factor, random fixed rate, average load, and phase delay parameter.	0.464	$9.7\ 10^{-6}$	38.91	4211
3. High load factor, random fixed rate and average load parameter.	0.711	$1.581\ 10^{-3}$	45.650	3781
4. High load factor, random fixed rate, average load, and phase delay parameter.	0.710	$1.782\ 10^{-3}$	45.970	3756

Table 4 summarizes simulation results for the first four experiments. The low load factor with random average loads gives the lowest benefit index value. In this case, the random time series parameters are average power demand and fixed rate tariff. If power demand peaks when RTP peaks, the customer experiences an increase in electricity costs compared to a fixed rate. Moving the power demand series with respect to the peak RTP series improves the benefits index by making the peak demand and price coincide less. High values of daily phase delay correspond to moving industrial operations outside the time of peak electricity usage, which may increase production costs due to increased labor expenses.

The high load factor demand series produces the highest benefit index values. The index does not improve significantly with changes in shift phase delay. The low variation in the daily load pattern increases the savings potential of the RTP tariff since most of the daily price cycle is lower than the fixed rate. The lower hourly rates produce savings while the RTP is below the fixed rate. As long as price spikes are of short duration, an industrial customer will realize cost benefits from using a RTP tariff if they have a high load factor. Facilities that are operated around the clock and have almost constant process electricity demands exhibit a high load factor.

Figures 3 and 4 show the cumulative probability distributions for the four benefit simulations. The low load factor simulation with no shift phase delay adjustment produces the lowest probability of positive benefit. (P=0.63, B>0) Adjusting the phase delay along with the average demand parameter improves this probability to P=0.72. The high load factor cases produce nearly identical positive benefit index probabilities with a value of P=0.76. These results indicate that industrial electrical loads that have high load factors can produce cost savings when a RTP tariff is applied. The savings are realized without instituting additional energy management programs. Low load factor demands can produce cost savings on

Figure 3. Cumulative Probability Distributions Comparing Low Load Factor Power Demand Having Random Price, and Average Demand with a Case Having Random Price, Average Demand, and Shift Phase Delay.

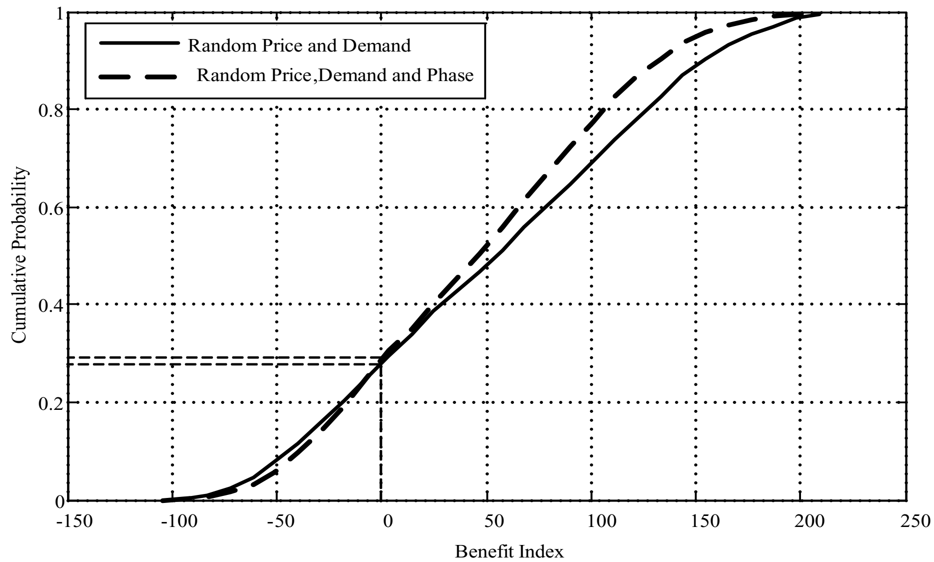
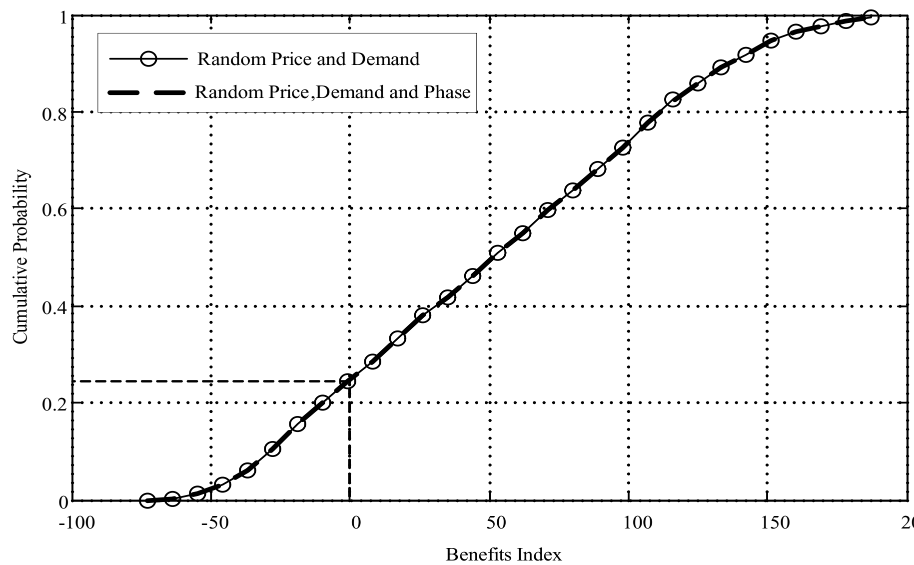


Figure 4. Cumulative Probability Distributions Comparing High Load Factor Power Demand Having Random Price, and Average Demand with a Case Having Random Price, Average Demand, and Shift Phase Delay.



an RTP rate, but may require extensive load control to achieve the benefit levels of a high load factor demands.

If the load pattern is highly correlated with the price pattern, electricity cost will increase on a RTP tariff. Peak shaving and load shifting based on projected prices minimize the risk of high cost consumption. However, instituting these load control programs could be costly and mitigate any potential savings from a rate switch.

Table 5 lists results from mean equality tests of the benefits experiments. The first two rows indicate that low load factor mean benefits are statistically less than high load factor mean benefits regardless of parameter variation in the load model. Comparing mean benefits between low load factor experiments 1 and 2 shows that delaying highly cyclic loads with respect to the RTP tariff produces a statistically significant improvement in the benefit means. High load factor experiments show no statistically significant difference between benefit means when load parameters vary. This result indicates that adjusting shift operations in high load factor demands will produce no statistically significant benefits when compared to high load factor demands without shift operation adjustment.

Experiments 5 and 6 examine the impact of power demand variations on the break-even normalized fixed rate. The histograms in Figures 5 and 6 show the simulation results.

The fluctuations of the power demand and the RTP increase the variability of the break-even fixed rate for the low load factor series. The break-even fixed rate varies 0.18 per unit (pu) over the range of simulation values. The load variations add to the average RTP rate and relate to the load changes. The high load factor simulation results in a very sharp price distribution, which is consistent with the low demand variation about the mean in this model. The break-even fixed rate is very near the average RTP for the analysis period for high load factor demands.

The presented methodology uses load models based on Fourier decomposition of actual load data with stochastic components to compute benefits. This technique ignores the impact of outliers in the original data series that may affect study results. It also assumes that operations remain cyclic over the study period. Using actual normalized power demand data to compute customer benefits eliminates these limitations but make it more difficult to identify parameters that relate to work processes.

Conclusion

Introducing real-time price tariffs to all customers creates opportunities for electricity cost saving in industrial operations. The shape and timing of the load time series relative to the price series impacts the potential benefits a business realizes from adopting a

Table 5.Mean Equality Test Results.

Experiment Means Compared	Z	Statistically Different α=0.05
1-3	-16.88	Yes
2-4	-5.590	Yes
1-2	-11.16	Yes
3-4	-0.256	No

Figure 5. Break-Even Fixed Rate Distribution for Low Load Factor Power Demand.

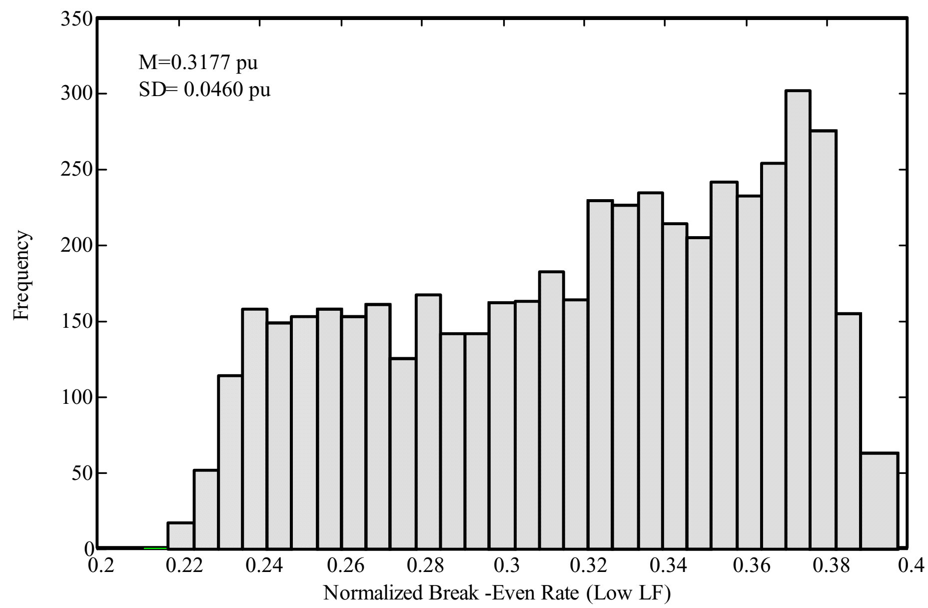
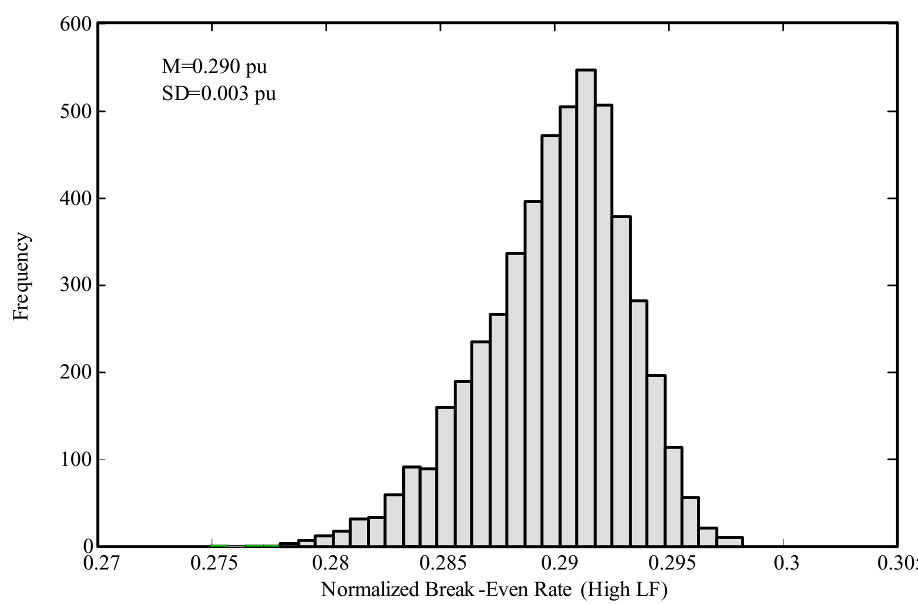


Figure 6. Break-Even Fixed Rate Distribution for High Load Factor Power Demand.



real-time price tariff. Results of Monte Carlo simulations using power demand mathematical models with high and low load factors indicate that higher load factor time series have a greater economic benefit potential. The high load factor power demand series exhibits a lower break-even fixed price when compared to the low load factor series. Industrial operations that operate around the clock and have a steady process load can save electricity costs by adopting a real-time rate without further investment in energy management or control systems. Using actual data to compute benefits could provide more accurate case studies but would eliminate analysis parameters. Future work will extend the analysis period of the experiments to cover an entire summer.

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