Estimating the Value of Service Using Load Forecasting Models

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1. Introduction

What is the actual value of electric service to customers? In this light, what is the optimal level of investment in generation, transmission, and distribution? What is the value of electricity reliability? These are complex and difficult questions for utility planners, executives, and regulatory agencies.

Estimates of the Value of Service (VOS) provide critical information to support customer-focused, value-based planning. VOS is particularly useful to determine the economically efficient level of investment in utility plant (generation, transmission, and distribution). VOS can also be used to evaluate the payoff for investments in technologies to better manage the grid, improve reliability, and provide service quality. The importance of reliability continues to grow rapidly with greater reliance on the internet economy and its associated dependence on a safe and reliable electric supply.

Reliable estimates of VOS have been difficult to determine given the number of parameters involved and the uncertainties that arise from the use of survey techniques. Planners have used integrated resource planning models (IRP) to design resource plans to minimize long-run revenue requirements subject to reliability criteria on number of hours of unserved energy and/or reserve margins. However, these values are not grounded with a customer VOS perspective. These models tend to produce only macro, high-level values for large assets such as central-station generation or transmission. Furthermore, these models fail to consider costs or benefits beyond those directly attributable to a utility asset.

Most VOS calculations rely on primary market research. These techniques either directly elicit customer estimates of the value lost from outages (e.g. willingness-to-accept compensation for an outage) or use methods to identify customer investments to reduce the impact of future outages (e.g. willingness-to-pay to avoid a negative outcome). In regulatory settings, VOS usually receives less focus compared to the utility's cost-of-service (COS) because COS is easier to quantify. Thus, avoided cost of service, defined in marginal terms, has been the primary metric for judging investment decisions in regulated utility arenas. While VOS techniques have been in use for decades, regulators have used VOS estimates primarily to define reliability levels, such as the U.K.'s use of Value-of-Lost-Load (VOLL). There is general agreement that VOS produces greater values than COS, including when customer survey techniques are used. The accepted approach in advanced resource planning is to equate the marginal VOS to the marginal COS (MVOS = MCOS), as this represents the "market" equilibrium point where the marginal customer value is equal to the marginal cost of providing that value.

In order to reduce the uncertainty in current VOS estimates, this paper presents a valuation approach to augment existing primary market research techniques. Economic theory shows that the consumer demand curve represents the consumers' willingness to pay for an assumed quantity demanded. Thus, the area under the demand curve for electricity offers an estimate of consumer value for the use of electricity. This paper uses econometric load forecasting models to demonstrate an alternate method for determining class level VOS estimates for customer use of electricity.

While the proposed method brings with it uncertainty, the use of multiple estimates - both survey-based and demand curve-based- coupled with methods to capture covariance of key variables (such as weather, economics, prices, and customer behavior), enables a comparison of results and should increase the confidence in the use of VOS estimates.

The paper proceeds with a brief review of the literature. That leads to a discussion on the load forecasting model and the process used to estimate VOS. From this, estimates of the VOS are provided for customer classes in the Duke Energy Carolina service area. These estimates are then compared to estimates derived from past VOS survey research. Finally, detailed recommendations are offered on grid-based data collection needs to extend VOS calculations for individual customers.

2. Literature

Several attempts have been made in the literature to develop estimates of VOS[1]. Eto (2001) provides a good review of past research into this field. Generally, past studies have been survey based; that is, they have relied upon primary research surveys of customers to obtain their views on the value of reliable electricity service. The focus of the surveys has been two-fold: obtain estimates of the costs imposed from past load interruptions and obtain estimates of customer willingness to pay to avoid an interruption / the amount they would accept in compensation for an interruption.

A study by Sullivan, et al. (2009)[2] provides a methodology for developing estimates based upon a meta-analysis of survey data collected through past primary research studies. After collecting survey results from 28 studies of utility customer views from across the United States, Sullivan, et al. (2009) implemented an econometric based approach to estimating damage functions. These damage functions were designed to capture differences in customer characteristics, interruption attributes, and environment or climate conditions. In addition, the damage functions also allow for differentiation of the estimates by regions of the country.

[1] Reports to note: J Eto, J Koomey, B Lehman, N Martin, E Mills, C Webber, and E Worrell, "Scoping Study on Trends in the Economic Value of Electricity Reliability to the U.S. Economy." LBNL Report No. LBNL-47911 (2001); L Lawton, M Sullivan, K Van Liere, A Katz, and J Eto. "A framework and review of customer outage costs: integration and analysis of electric utility outage cost surveys." LBNL Report No. LBNL-54365. (November 2003); Kristina Hamachi LaCommare and Joseph H. Eto. "Understanding the Cost of Power Interruptions to U.S. Electricity Consumers," LBNL Report No. LBNL-55718 (September 2004); London Economics. "Estimating the Value of Lost Load: Briefing paper prepared for the Electric Reliability Council of Texas, Inc." London Economics International LLC (June 17th, 2013); The Brattle Group "Approaches to setting electric distribution reliability standards and outcomes," The Brattle Group, Ltd. (January 2012); and Michael J. Sullivan, Matthew Mercurio, and Josh Schellenberg. "Estimated Value of Service Reliability for Electric Utility Customers in the United States" LBNL Report No. LBNL-2132E (June 2009).

[2] Michael J. Sullivan, Matthew Mercurio, and Josh Schellenberg (June 2009).

In a recent report conducted for ERCOT, London Economics (2013) provided a critical review of past research into VOS[3]. In addition to acknowledging the difficulty associated with customers developing their own VOS estimates, London Economics (2013) points out that VOS estimates are extremely sensitive to factors like customer type, outage duration, time of an outage, and advance notification of an outage.

In the London Economics (2013) report, past study methodologies are categorized into four groups: revealed preference (past spending to avoid interruption), stated choice surveys (contingent valuation and conjoint), macroeconomic estimates (e.g., GDP/MWH), and case studies (review impact of actual events). While each of these approaches is useful and can help triangulate on potentially reasonable VOS estimates, London Economics (2013) points out the weaknesses of each.

For example, the revealed preference approach, while using actual customer data, is only relevant if customers actually invested to mitigate exposure to interruptions. This limits the applicability of the approach. The stated preference method relies on consumer responses to surveys. While survey questions allow for more input on aspects such as the impact of outage duration, the results can be unreliable since consumers may not be able to reasonably relate their perception of the impact of outages to monetary values. The macroeconomic approach may be easy to implement, but represents too broad of a measurement. And finally, the use of case studies can provide great insights, but the results are costly to obtain and have limited applicability to a general understanding of the VOS.

London Economics (2013) concludes that estimating VOS is a challenging task that ultimately requires the use of a survey of customers. Past research into VOS has typically been based on primary research of customers. Estimates have not been attempted through the use of load forecasting demand functions.

3. A New VOS Approach

In economic theory, the demand curve for a good or service represents what a consumer is willing to pay for a certain quantity of a good or service at a given price. For electricity markets, if a consumer only consumes one kWh, the demand curve will represent the maximum amount that the consumer would pay for one kWh[4]. In that context, this equates to the VOS associated with the consumption of that first kWh. Obviously, electricity users consume a lot more than one kWh. But, at a given price for electricity, the area under the demand curve for the volume of kWh consumed at that going price will represent the VOS for that volume of consumption.

[3] The London Economics (2013) study actually focused on the value of lost load (VOLL) which is another way to examine VOS.

[4] See page 99 of Edwin Mansfield. Microeconomics, 6th Edition. New York: W.W. Norton & Company, 1988 for a discussion of consumer surplus. While this is not the same as willingness to accept compensation, the area under the demand curve represents the implied value from consumption of the good as an alternate measure to survey based estimates of value.

Given a demand curve for electricity like that shown in Figure 1 below, the area identified by ABCD represents the value of the service (VOS) to the consumer. Note this area is larger than just the area found by multiplying the price times the quantity since it also includes consumer surplus.

Now, using an econometric model of the demand curve, the VOS can be estimated at the margin and in total. The value along the line AB represents the VOS of the marginal unit. If a consumer is forced to reduce usage, the marginal VOS would be expected to increase (the value on the line increases as Q declines).

Taking a residential demand equation such as this:

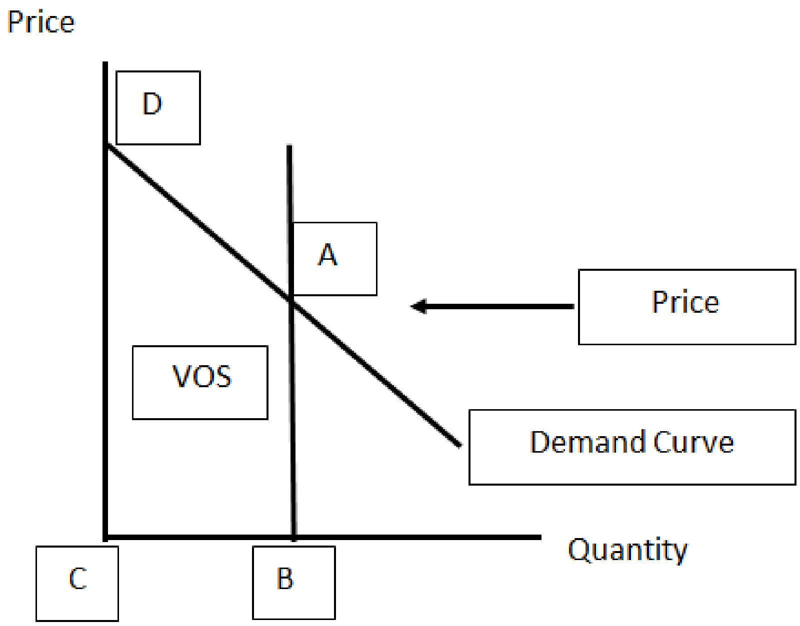
(1) $Q = a + b \cdot P + c \cdot \text{Income} + d \cdot W + \varepsilon$

where:

Q	=	quantity or kWh
P	=	price per unit
Income	=	consumer income
W	=	weather and any other variables
a	=	intercept
b, c, & d	=	slope parameters
ε	=	error

Figure 1

Graphical View of VOS



The inverse of the equation becomes:

(2) P(Q) = (Q – a - c · Income - d · Weather)/b

Then, the VOS area can be estimated by taking the integral of the demand equation for the volume of consumption.

(3) $\int P(Q)dQ =$ ∫((Q – a - c · Income - d · Weather)/b) *d*Q

From (3), one can take the value of the integral over the range to the quantity consumed and divide by the volume to get an average VOS/kWh. However, it will be important to show how the integral changes as quantity Q declines and how the VOS/Q changes with marginal changes in Q.

For electricity, a number of factors impact the level of consumption. For example, a residential customer's usage will vary depending upon factors such as: income level, the efficiency of the appliances in the home, the weather, the size and thermal integrity of the home, and the type of appliances being used. Similarly, a commercial customer's usage will vary significantly based upon factors such as: the type of business, the size of the building, the efficiency of the equipment in the business, the volume of business, and the number of employees. Industrial or manufacturing facilities possess the most variability when one considers how much end-user energy consumption can change from one industry to another. In addition to the same types of factors affecting commercial usage, the type of industry plays a major role in the amount of energy consumption. For example, steel plants and chemical manufacturers will typically use a lot more energy than a furniture factory. However, customer energy use (even within the same industry) still depends on the relative sizes of the facilities.

As part of the utility planning process, electric utilities prepare forecasts of future energy usage by customer class. These forecasts often look twenty to thirty years into the future. Over the past few decades, the methodology employed to prepare a forecast has evolved from simple trend lines to econometric models, to end-use models, to hybrid econometric/end-use models and statistically-adjusted end-use (SAE) models. One feature of econometric based forecasting models is these models can provide an alternate view of the VOS. In the process of estimating price elasticity, the econometric based electric load forecasting model represents the demand curve for electricity, holding other variables constant. Using equations (1) through (3) above, one can employ the coefficients from a load forecasting model to estimate the VOS. This forms the basis for the following process of VOS estimation using actual demand forecasting models of Duke Energy Carolinas.

4. VOS Application Using Duke Energy Carolinas' Forecasting Models

Duke Energy Carolinas has prepared load forecasts for decades using econometric based models. The general model structure involves the development of econometric models for each class: residential, commercial, and industrial. The industrial class includes models for major industry groups, e.g., chemical, primary metals, textiles, etc. Using the forecasting models for the residential and commercial classes, as well as for one of the major industry groups, we can estimate VOS as implied by the estimate of the demand function. For Duke Energy Carolinas, the residential sector is modeled linearly on a use per customer basis. For the commercial sector and the industry group, electric usage is modeled for the total class or group using a log-linear relationship. These modeling differences can impact the shape of the estimates, though the processes are similar[5]. Table 1 provides the coefficient estimates for each of the models.

Table 1
Coefficient Estimates

	Residential kWh/Customer/Day	LN(Commercial MWH)	LN(Industrial MWH)
Intercept	16.24		
Heating Degree Days	0.014297476		
Cooling Degree Days	0.024556869		
Appliance Stock x Real Disposable Income/Capita (1)	0.0000000145188269194		
Appliance Stock x Real Electric Price (1)	(0.0000437023704676)		
Real Price of Natural Gas	0.140737168		
Intercept		5.351481587	8.997335708
Heating Degree Days (2)		0.00004399967	(0.00004864)
Cooling Degree Days		0.000293522	0.00005427
LN(Real Disposable Income)		0.853974652	
LN(Real Electric Price)		-0.240285671	-0.312070781
LN(Real Gross Domestic Product for NAICS 325)			0.496976457

(1) Applicance stock represents an appliance saturation and efficiency weighted level of connected appliance load.
(2) Note: the coefficient in the industrial model for HDD is negative inducating the presence generation on-site that operates during colder weather.

[5] The integration for the linear model is more straightforward than that for the log-linear model.

Residential VOS per Customer

Using the model coefficients, we estimate the VOS for an average residential customer in the Duke Energy Carolinas service area as shown in Table 2.

Table 2 Estimates of Residential Value of Service			
	kwh	VOS	VOS Cents
Season	per Day	$ per Day	per kWh
Winter	42.25	21.99	52.05
Spring	31.36	12.53	39.98
Summer	42.37	22.06	52.08
Fall	32.92	13.71	41.65

This table shows how the residential consumer's VOS varies by season[6]. These are average values for the season. As one would expect, usage in the seasons with greater exposure to extreme weather are valued higher. All VOS values have been converted to a 2014 dollar level.

Going further, one can see from Tables 3 to 5 how the estimates vary with the weather and with income levels. Table 3 provides estimates as the level of HDD increases, whole Table 4 presents similar information over a range of CDD values. Table 5 provides a view into how VOS adjusts with alternate levels of income.

Table 3 Estimates of Residential Value of Service			
	kwh	VOS	VOS Cents
HDD	per Day	$ per Customer/Day	per kWh
0	19.98	5.47	27.37
100	21.41	6.20	28.95
500	27.12	9.56	35.25
1000	34.27	14.79	43.14
1500	41.42	21.14	51.03

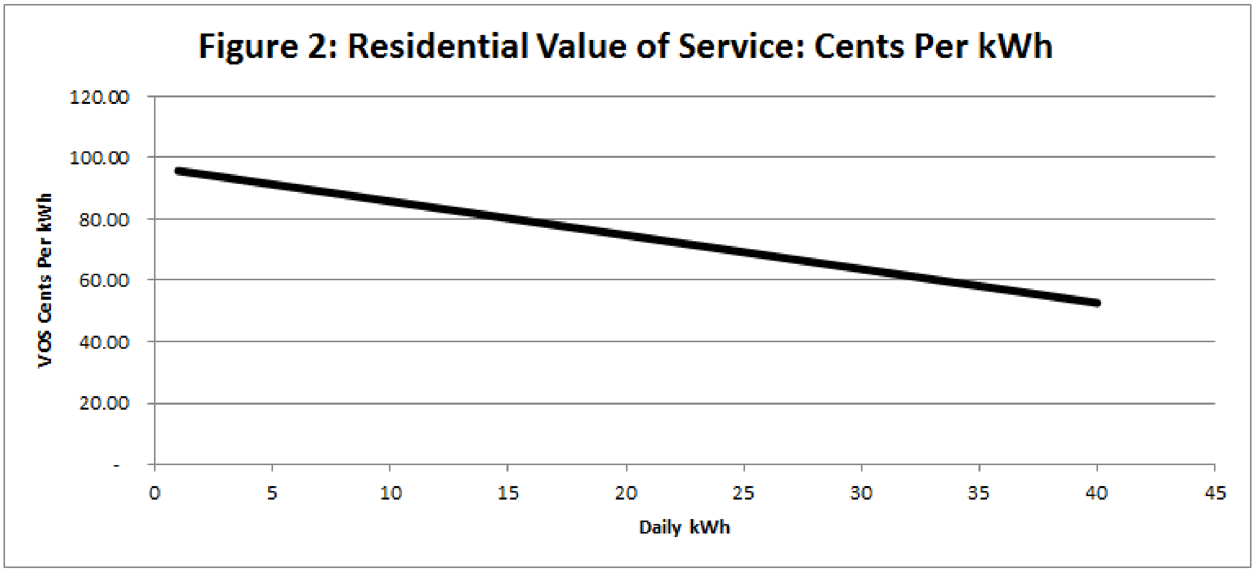
[6] The seasonal reference is an approximation. The seasons actually represent the four quarters of the year. These approximate the seasons since, for example, the billing degree days for the first quarter (January through March) would actually include a major portion of December.

Table 4 Estimates of Residential Value of Service			
	kwh	VOS	VOS Cents
CDD	per Day	$ per Day	per kWh
0	19.98	5.47	27.37
100	22.43	6.75	30.08
200	24.89	8.16	32.79
500	32.25	13.20	40.91
1000	44.53	24.25	54.46

Table 5 Estimates of Residential Value of Service				
		kwh	VOS	VOS Cents
Season	Income	per Day	$ per Day	per kWh
Winter	$ 30,000	41.42	21.14	51.03
Winter	$ 50,000	45.15	24.90	55.14
Winter	$ 100,000	54.47	35.64	65.42
Summer	$ 30,000	39.62	19.43	49.04
Summer	$ 50,000	43.35	23.04	53.15
Summer	$ 100,000	52.67	33.41	63.44

As expected, Table 5 shows how the VOS increases with income. It should be noted that one cannot tell if summer usage is valued more than winter usage due to the fact that the levels of HDD and CDD have different levels of importance that can be affected by the saturation of electric heat vs. air conditioning. To truly understand the differential valuation would require conducting this type of analysis at the individual level for those with gas heat and central air as well as those with electric heat and central air. This will be discussed further in the section on potential extensions of this type of analysis.

Figure 2 below provides a visual look at how the VOS per kWh varies with the level of daily usage. This is looking that the VOS during a winter season. The implication is that those first few kWh are valued a lot higher than at the point where the consumer already has a positive level of consumption.



Commercial VOS

Turning to the commercial sector, the complexity increases since the model is in a log-linear form and it represents the total commercial class level of load. Commercial customers are not homogeneous which makes the estimates more of an average. To truly gain insight for specific types of commercial customers requires developing models and processes at the individual customer level. Using the model estimates provided in Table1, values of VOS were developed for an average commercial customer as shown in Table 6 for each season. Again, the heavier weather months see higher values.

Table 6
Estimates of Commercial Value of Service

Season	kwh per Day	VOS $ per Day	VOS Cents per kWh
Winter	222	320.54	144.62
Spring	226	338.53	150.04
Summer	270	401.64	148.89
Fall	224	336.67	150.38

Tables 7 to 9 provide additional insights at alternate levels of HDD and CDD as well as at different levels of commercial economic activity as measured by real disposable income ($MM).

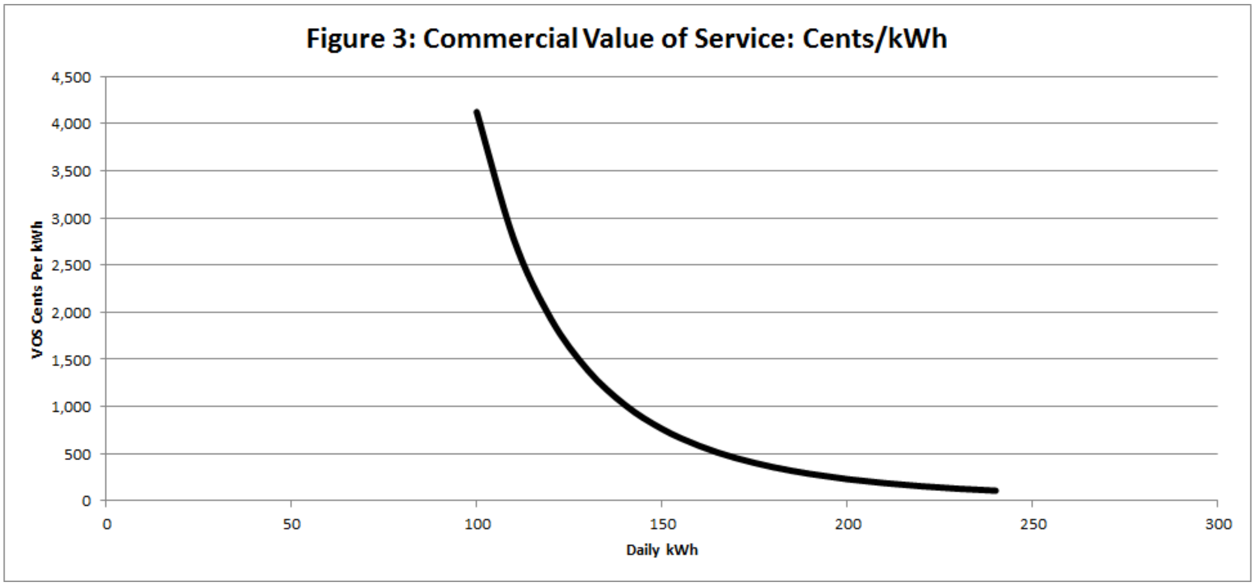
Table 7		
Estimates of Commercial Value of Service		
	Kwh per Day	VOS
HDD	per Customer	$ per Customer/ Day
0	208.0	309.09
100	208.9	310.46
500	212.7	315.97
1000	217.4	323.00
1500	222.2	330.18

Table 8		
Estimates of Commercial Value of Service		
	Kwh per Day	VOS
CDD	per Customer	$ per Customer/ Day
0	208.03	249.67
100	214.22	257.11
200	220.60	264.77
500	240.91	289.14
1000	278.99	334.84

Table 9			
Estimates of Commercial Value of Service			
	Regional	kwh	VOS
Season	Disposable Income	per Day	$ per Customer/ Day
Winter	$ 200,000	252.35	302.87
Winter	$ 250,000	305.32	366.45
Winter	$ 300,000	356.76	428.18
Summer	$ 200,000	213.15	255.82
Summer	$ 250,000	257.90	309.52
Summer	$ 300,000	301.34	361.67

Tables 7 and 8 demonstrate how the VOS for an average commercial customer increases as the effect of weather rises. And, Table 9 provides insight on how that VOS rises as the level of commercial economic activity ramps up.

The VOS for an average commercial customer for the daily level of kWh is provided in Figure 3. Notice the curvature of this result relative to that in the residential model. This is a direct outcome of the underlying functional form of the forecasting equation, linear vs. log-linear.



Industrial VOS

Duke Energy Carolinas has developed econometric based forecasting models for many industry groups. For this research, the purpose here is to show that the process of using econometric forecasting models can be applied to derive estimates of the VOS. The chemical industry is one of the key industries within the Duke Energy Carolinas service area. For that reason, the forecasting model for the chemical industry is utilized to derive industrial VOS estimates realizing that these values do not reflect the full industrial sector.

As with the commercial class, the chemical industry sector is not homogeneous. Customers can vary greatly in size, even though they may be classified in the same industry. As before, to truly understand the VOS for the industry requires investigating this at the customer level. Using the log-linear model coefficient estimates provided in Table10, values of VOS were developed for an average chemical industry customer as shown in Table 6 for each season.

Table 10
Estimates of Industrial Value of Service

Season	kwh per Day	VOS $ per Day	VOS Cents per kWh
Winter	13,337	7,386	55.38
Spring	14,768	8,212	55.61
Summer	15,631	8,766	56.08
Fall	14,292	7,810	54.65

While the VOS cents per kWh estimates are much lower than those for an average commercial customer, due to the higher volumes, the VOS daily values are much higher. This indicates that the industrial customer might have more options to adjust to a minor reduction in usage, but that a total shut-down has more serious consequences.

Tables 11 to 13 provide additional insights at alternate levels of HDD and CDD as well as at different levels of industrial economic activity as measured by real gross domestic product for the chemical industry ($MM).

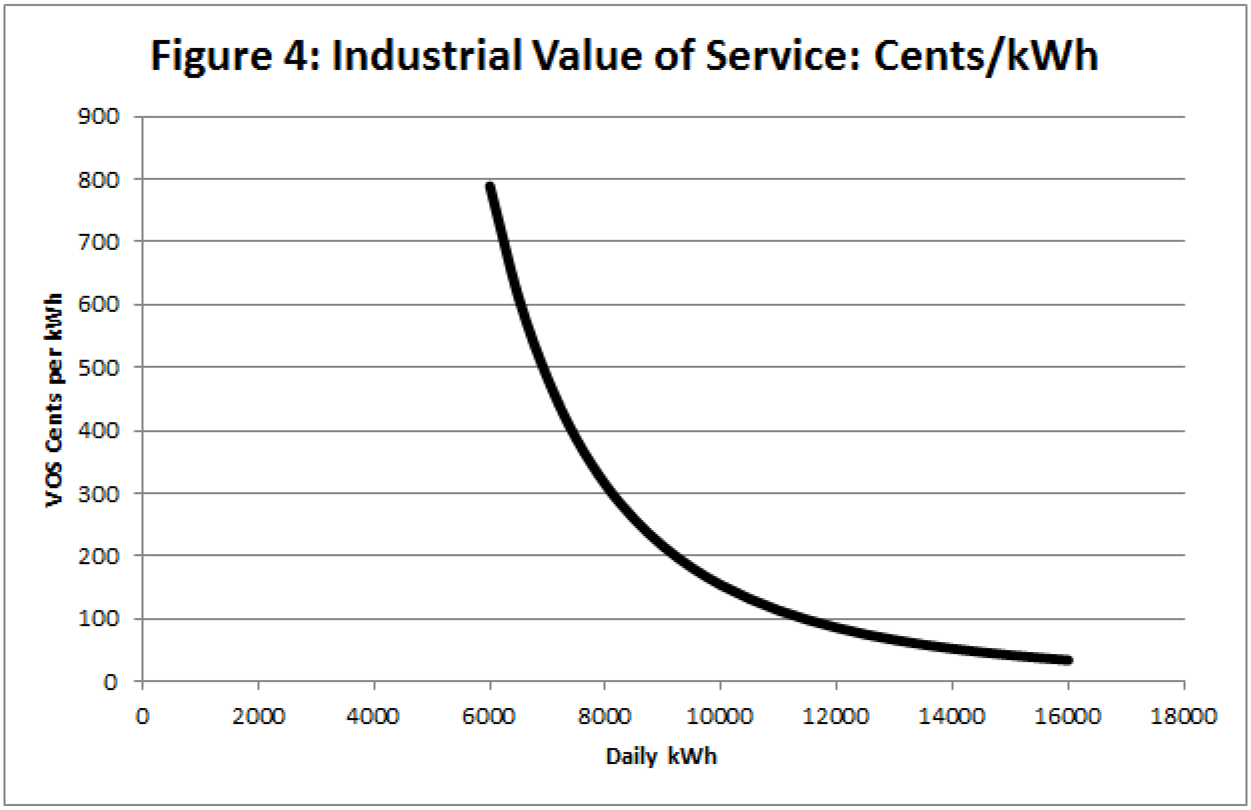
Table 11 Estimates of Industrial Value of Service		
HDD	Kwh per Day per Customer	VOS $ per Customer/Day
0	14,650.2	$ 8,357
100	14,579.1	$ 8,317
500	14,298.1	$ 8,156
1000	13,954.6	$ 7,960
1500	13,619.3	$ 7,769

Table 12 Estimates of Industrial Value of Service		
CDD	Kwh per Day per Customer	VOS $ per Customer/Day
0	14,650.15	8,357
100	14,729.88	8,403
200	14,810.05	8,448
500	15,053.17	8,587
1000	15,467.26	8,823

Table 13 Estimates of Industrial Value of Service			
Season	Real GDP NAICS 325	kwh per Day	VOS $ per Customer/Day
Winter	$ 7,000	14,784.55	8,433.82
Winter	$ 7,500	15,300.27	8,728.01
Winter	$ 8,000	15,798.97	9,012.49
Summer	$ 7,000	13,160.20	7,507.21
Summer	$ 7,500	13,619.26	7,769.08
Summer	$ 8,000	14,063.16	8,022.30

Tables 11 and 12 demonstrate how the VOS for an average chemical industry customer changes with the severity of the weather. As previously noted, decreases in VOS are associated with an increase in HDD. This occurs because chemical companies' need to turn on alternate generating facilities to create steam which can produce electricity as a by-product, hence reducing dependence on utility provided generation. The converse occurs for CDD. Table 13 provides insight on how that VOS rises as the level of industrial economic activity increases.

The VOS for an average chemical industry customer for the daily level of kWh is provided in Figure 4. As for the commercial class, there is a similar curvature to this relationship. This is a direct outcome of the underlying log-linear functional form of the forecasting equation.



5. Comparison to an Alternate View

The approach conducted in the Sullivan, et al. (2009)[7] study produced estimates of the VOS for three classes: residential customers, small commercial and industrial (C&I) customers, and medium and large C&I customers. While the categories may be different and the lengths of outages do not necessarily correspond to the values developed above, they do provide an opportunity for comparison.

Table 14 is taken from the Sullivan, et al. (2009)[8] study. It provides estimates of the VOS for each of the customer groups at different levels of outage. Keep in mind that Sullivan, et al. (2009) focused on estimating damage functions to represent the VOS as viewed by a customer facing an outage. The values in the table are in 2008$. These have to be adjusted for inflation between 2008 and 2014 to make them comparable to the dollar values derived from the econometric forecasting models presented in the previous tables.

[7] See Michael J. Sullivan, Matthew Mercurio, and Josh Schellenberg (June 2009).
[8] See Michael J. Sullivan, Matthew Mercurio, and Josh Schellenberg (June 2009), page xxvi.

Table 14

Table ES- 5. Estimated Average Electric Customer Interruption Costs US 2008$ Anytime By Duration and Customer Type

Interruption Cost	Interruption Duration				
	Momentary	30 minutes	1 hour	4 hours	8 hours
Medium and Large C&I					
Cost Per Event	$6,558	$9,217	$12,487	$42,506	$69,284
Cost Per Average kW	$8.0	$11.3	$15.3	$52.1	$85.0
Cost Per Un-served kWh	$96.5	$22.6	$15.3	$13.0	$10.6
Cost Per Annual kWh	9.18E-04	1.29E-03	1.75E-03	5.95E-03	9.70E-03
Small C&I					
Cost Per Event	$293	$435	$619	$2,623	$5,195
Cost Per Average kW	$133.7	$198.1	$282.0	$1,195.8	$2,368.6
Cost Per Un-served kWh	$1,604.1	$396.3	$282.0	$298.9	$296.1
Cost Per Annual kWh	1.53E-02	2.26E-02	3.22E-02	$0.137	$0.270
Residential					
Cost Per Event	$2.1	$2.7	$3.3	$7.4	$10.6
Cost Per Average kW	$1.4	$1.8	$2.2	$4.9	$6.9
Cost Per Un-served kWh	$16.8	$3.5	$2.2	$1.2	$0.9
Cost Per Annual kWh	1.60E-04	2.01E-04	2.46E-04	5.58E-04	7.92E-04

The load forecasting models used in developing VOS estimates in this paper reflect an implied VOS. Table 15 provides a summary comparison of the range of values from the Sullivan, et al. (2009) versus those derived from the load forecasting models.

Table 15
VOS Estimate Comparisons

	Sullivan Study				Forecast Model		
	Cost Per Event VOS Estimates				Model Based Implied VOS Estimates		
Class	Momentary	1 Hour	8 Hours		Class	Cost Per Day Range	
Residential	$ 2.36	$ 3.71	$ 11.91		Residential	$ 19.43	$ 54.46
Small C&I	$ 329.18	$ 695.44	$ 5,836.56		Commercial	$ 255.82	$ 428.18
Medium and Large C&I	$ 7,367.89	$ 14,029.09	$ 77,840.29		Industrial	$ 7,507.21	$ 9,012.49
Note: All values are in 2014 $.							

The comparison of these results reveals the following:

- The residential model based estimates far exceed those from the Sullivan Study. The model based estimates are intended to reveal implied value, while the Sullivan Study estimates are based on market research. This may point to the difficulty of obtaining a residential customer's estimate of damage through a survey.

- The small C&I and the medium and large C&I estimates for a momentary outage from the Sullivan Study seem to correlate well with the commercial and industrial model based estimates.
- The small C&I and the medium and large C&I estimates for longer periods of time from the Sullivan Study far exceed the model based estimates. However, the model based estimates reflect an average value over a quarter assuming a normal daily level of usage. The model based value of service can increase dramatically into the tens of thousands of dollars for commercial and industrial customers if the customer can only obtain 10 percent of their normal level of energy. In that case, the customer places a high value on an incremental amount of energy.

6. Conclusion and Potential for Future Research

The research presented in this paper provides an alternate approach for estimating the VOS using utility forecasting models. While the results found here just scratch the surface, they do point to a reasonable method for utilities to obtain estimates of the VOS. The advantages of this approach are that it is a less costly method than primary research and it provides an implied customer perception of value that survey methods cannot provide. At the same time, survey based methods possess more flexibility for assessing perceptions that vary over the length of an outage. The bottom line is that both methods can be useful in triangulating on a concept that is very difficult to estimate.

Further gains in the model based approach are readily apparent. By developing econometric models of consumer demand for sub-groups of customers (e.g., residential space heating, residential air conditioning, and any number of types of commercial and industrial customers), one can easily obtain detailed estimates of the implied VOS. Data from load research studies that collected interval data could be used to examine the hourly level of the VOS. Data from utility residential customer appliance saturation surveys could also be used to further understand how the VOS varies based upon the nature of the individual customer's appliance ownership as well as type of residence and economic situation. Other segments or characteristics that could be examined include customers in Energy Star certified buildings, customers in older traditional buildings, and impacts of alternate rate designs.

Ultimately, with the collection of more granular data on all customers through smart grid applications and data collection processes, it would be possible to estimate the VOS for each customer. For utilities, this becomes extremely important for identifying those customers that place greater value on service and reliability than others. This impacts the locational need for distribution system upgrades and can help identify those customers more likely to participate in energy efficiency and demand response programs as well as those more likely to be interested in distributed energy resources including storage and renewable sources of energy.

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