An Empirical Model for Predicting Electric Energy Efficiency Resource Acquisition Costs in North America: Analysis and Application

John Plunkett, Theodore Love, and Francis Wyatt, Green Energy Economics Group, Inc.

ABSTRACT

Energy efficiency resource standards (EERS) are becoming the policy tool of choice for stimulating investment in demand-side substitutes for electricity supply. After summarizing published information on savings and expenditures by efficiency resource portfolios across the United States over the past five years, this paper presents the results of multiple regression analysis of actual and planned annual electric energy savings and spending by over thirty portfolio administrators in the United States and Canada. The estimated coefficients reveal two opposing forces predicted by economic theory for deepening efficiency resource acquisition: economies of scale and diminishing marginal returns. The empirical model also found statistically significant covariance, the measurement of how variables change together, between efficiency resource costs and temporal, sectoral, and geographic characteristics of efficiency portfolios. Finally the paper illustrates how the statistical model can be used to predict future efficiency resource acquisition costs corresponding to energy savings targets and thus expected budgets in any jurisdiction or utility service area.

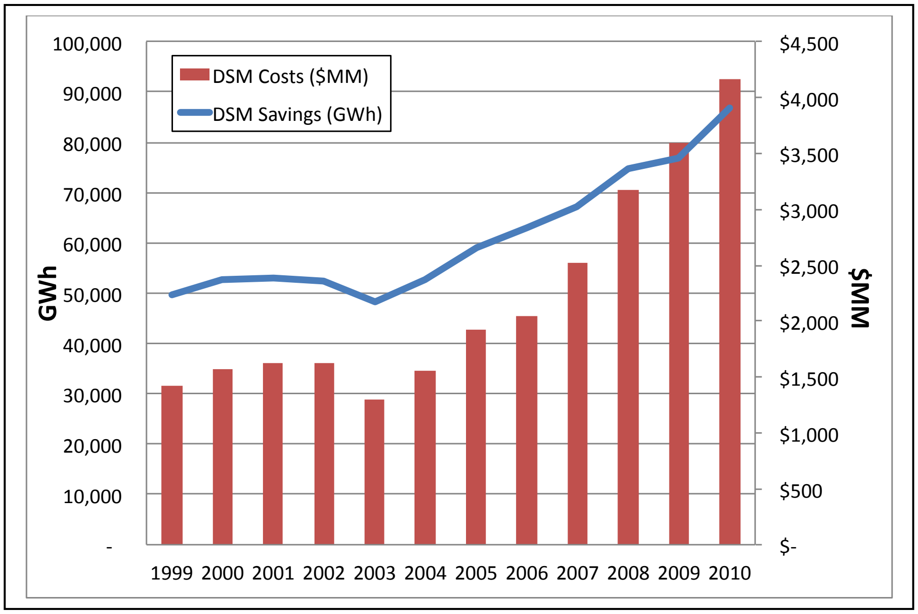
Background

Utilities across North America have been relying on energy efficiency investment to reduce electric energy and capacity requirements for over a quarter century. This trend is expected to accelerate as policymakers look to energy efficiency as the resource of choice to cost-effectively displace new and existing carbon-based electricity supply. Two recent reports by the American Council for an Energy-Efficient Economy (ACEEE) document the ascendance of Energy Efficiency Resource Standards (EERS) as a means of establishing multi-year targets for electric energy savings (Sciortino, Nowak, et al. 2011; Nowak et al. 2011). Absent detailed "bottom-up" studies of achievable efficiency savings and their associated costs, it has been difficult for policy makers, regulators, utilities, and other stakeholders to establish expectations surrounding the range of potential costs of attaining EERS savings goals.

Historical Data

The US Department of Energy's Energy Information Administration (EIA) tracks statistics on demand-side management (DSM) through its Annual Electric Power Industry Report, Form EIA-861. Both reported electric savings from and expenditures on energy-saving DSM programs have steadily and significantly increased over the past decade (Figure 1).

Figure 1. DSM Activity in the United States



Source: US EIA 2011

ACEEE has compiled and analyzed these results in its annual State Energy Efficiency Scorecard, beginning in 2006. ACEEE's scorecards were originally confined to US EIA statistics; recently ACEEE has expanded the scope of data collection beyond published EIA results. ACEEE's latest scorecard showed 48 out of 50 states budgeted a total of $4.6 billion for energy efficiency in 2010, and achieved incremental, combined annual savings of 13,147 GWh in 2009 (Sciortino, Neubauer, et al. 2011). Although the three most recent ACEEE scorecards encompass the entire country, they do not provide cost data corresponding to reported savings beyond 2006 and 2007. Nor does ACEEE separately report portfolio savings and cost information for residential and non-residential sectors, for which efficiency opportunities differ significantly. The EIA data, although collected at the utility level, has not always been consistent and lacks explanatory details. To provide a more useful data analysis platform, Green Energy Economics Group (GEEG) has gathered primary data on costs and performance reported by selected North American portfolio administrators to state and provincial utility regulators.

Looking Ahead

U.S. federal equipment efficiency standards enacted in 2007 for a variety of products and equipment, and lighting in particular, will significantly change the baseline market conditions confronting DSM program design (US House, 2007). New equipment standards will have the dual effects of lowering forecasts of future electricity demand, and reducing the amount of savings that DSM programs can achieve beyond market forces. Operating in tandem with more energy-efficient building codes and the aforementioned equipment standards, technological change is expected to increase the efficiency of a wide variety of products and equipment available in the next two decades. This higher efficiency will reduce the energy intensity of major household and business electricity end uses. Given this fundamental shift in savings opportunities and costs, past performance alone is no longer as likely as it once might have been to be a reliable predictor of future energy efficiency resource costs.

Economic Theory

Microeconomic theory postulates that the two opposing forces of economies of scale and diminishing marginal returns should, in the context of energy efficiency, influence the costs of increasing savings from efficiency program portfolios. With regard to economies of scale, portfolio administrators experience decreasing unit costs as they spread fixed development, as well as marketing and administration costs, across more participants and greater aggregate energy savings. The second force, diminishing marginal returns, will likely have an effect at some point on portfolio administrators' expansion path—specifically administrators should expect increasing unit costs. Two mutually reinforcing reasons can explain this. First, achieving greater savings as a percentage of total consumption eventually requires investment in more expensive efficiency measures. For example, the consumer's price premium for top-efficiency equipment is greater than that for mid-efficiency equipment. Second, decades of program experience show that programs must offer progressively higher financial incentives to induce higher levels of participation among harder-to-reach customers. This second dynamic combines with the first to raise costs disproportionately, since it is generally not possible for portfolio administrators to engage in "price discrimination" among participants—that is, programs must pay the higher incentives to all participants, not just to those customers that are harder to reach.

Data Collection

Efficiency savings can be compared across jurisdictions by first dividing incremental annual electric energy savings reported in any one year by corresponding electricity sales. Efficiency spending can be compared among jurisdictions either in terms of scale or yield. To compare spending between service areas, expenditures are divided by annual energy sales for each service area. To compare savings yields from DSM investment, annual expenditures are divided by annual savings to calculate the portfolio administrator's cost to acquire an annual kWh of electricity savings.

Spending and savings data were collected from a non-random sample of state and provincial regulatory filings. Sales data came from the US EIA or annual reports filed by program administrators. When possible, the savings data chosen were net of free-ridership, spillover, and line loss (that is, net at meter) effects. In addition, great care was taken to make sure that only costs directly related to a given savings were included. Any portfolio-wide costs not associated with a specific program were allocated between residential and non-residential sectors, based on the percentage of spending for that sector in that year. At the time that data was collected, the US EIA had not yet released statistics on 2010 utility level electricity sales. In order to maintain consistency across the data set, 2010 energy savings were taken as a percentage of 2009 energy sales.[1]

GEEG collected historic cost and savings data on efficiency portfolios reported to regulators for states with the greatest savings as a percentage of sales, particularly those in California and Northeastern states with mature portfolios; for Midwestern and Western states with significant efficiency portfolios (Iowa, Nevada, and Wisconsin); and for the contiguous jurisdictions of Arkansas, Texas, and Oklahoma. Where possible, GEEG obtained cost and saving data separately for the residential and non-residential sectors. GEEG also collected

[1] 2009 savings were also taken as a percentage of 2009 sales.

efficiency spending and savings data for two Canadian provinces, British Columbia and Nova Scotia. Finally, GEEG assembled the latest information available on future plans for electric end use efficiency investment in several states and provinces that have mature portfolios.

Observations Based on Visual Inspection: Energy Efficiency Savings Tiers

The state level results showed that annual energy savings as a percentage of sales varies widely, both geographically and over time. Looking at savings as a percent of sales from highest to lowest, performance can be classified into four tiers.

Tier 1 (≥1.5%): In the top tier, states are achieving at or near 2% of sales. It contains nine program years of experience: California, for four out of the past five years; Vermont, for three out the past four years; and Connecticut as of last year.

Tier 2 (≥0.67% and <1.5%): States in the second tier are saving at or near 1% of annual sales, with annual savings ranging from 0.67% to 1.5% of sales. In addition to earlier years' performance by California, Vermont, and Connecticut, this group also has data from 60 program years of experience with efficiency portfolios in Iowa, Maine, Massachusetts, Nevada, New York, Rhode Island, Hawaii, the Pacific Northwest, British Columbia, and Nova Scotia.

Tier 3 (≥0.33% and <0.67%): States with savings at or near 0.5% of sales fall into the third tier. This group comprises 25 program years of results, and includes savings in even earlier years for states in the first two tiers, plus Arkansas, New Jersey, and Wisconsin.

Tier 4 (<0.33%): States with savings less than 0.33% of sales fall into the lowest tier. This group saved approximately 0.25% of sales, and contains earlier results for some states with performance in Tier 3, as well as Texas and Arkansas.

As is clear from the program year data, many states with DSM portfolios in the top two performance tiers have progressed through lower tiers over time. Also evident from program year performance data is that moving up from one tier to the next is common, especially to and from the second tier. For example, Connecticut increased annual savings from 0.37% to 1.52% of sales between 2003 and 2010, moving from Tier 3 to Tier 1. Nova Scotia recently went from 0.17% of sales in 2008 (Tier 4 results), to 0.68% of sales in 2010 (Tier 2 results). These observations support the feasibility of ramping up utility investment over time. Further examination of the data was needed to establish a model for estimating costs, as portfolio administrators gain experience and navigate through performance tiers (GEEG 2011).

Multiple Linear Regression Analysis

The next step was to develop an empirical model that predicts energy efficiency resource acquisition costs per kWh of annual savings as a function of four types of variables:

- Savings depth
- Time
- Customer sector
- Location

The spending and savings data were prepared so that each data point was for a year, program administrator, sector (residential or non-residential), the 2011 dollar spent per annual kWh (2011$ / kWh-yr), and the savings as a percentage of sales.[2] Next, calculated fields and dichotomous (binary or "dummy") variables were added for each data point. Table 1 provides a list of all the fields in the data set.

Table 1. Fields in Regression Data Set

Variable	Designation	Definition
Country	Country	The country in which the energy efficiency activity occurred. This was either the United States or Canada.
State	State	The state (for the United States) or the province (for Canada) in which the energy efficiency activity occurred.
Program Administrator	Admin	The energy efficiency program administrator.
% Savings	Per_Sav	Incremental annual savings as a percentage of applicable sales.
$ / kWh-yr	Dol_kWh_Yr_2011	The program administrator's costs, in 2011$, per incremental annual kWh.
New England	NE	Flag for whether the administrator is in New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont). 0 for false, 1 for true.
California	CA	Flag for whether the administrator is in California. 0 for false, 1 for true.
Planned Spending and Savings	Planned	Flag for whether the spending and savings are planned. 0 for false, 1 for true.
Year	Yr	The year in which the energy efficiency activity took place
First Year	Yr_1	The first year in which data were collected for a given program administrator.
Maturity	Maturity	The current year of a data point, minus Yr_1
Residential	Res	Flag for whether the sector is residential. 0 for false, 1 for true.
Non-residential	Nonres	Flag for whether the sector is non-residential. 0 for false, 1 for true.
Year in 2006 - 2008	Yr_06_08	Flag for whether the year is any of 2006, 2007, or 2008. 0 for false, 1 for true.
Year in 2009 - 2011	Yr_09_11	Flag for whether year is any of 2009, 2010, or 2011. 0 for false, 1 for true.

Outliers were identified within this data set as any data point that had 2011$ / kWh-yr greater than one dollar ($1). This identification resulted in the removal of eight data points, all with savings as a percent of sales below 0.25%. The resulting data set had 473 data points and captured the full range of portfolio savings performance, from a low of 0.02% to a high of 4.17%. For 219 pairs of program administrator and year (436 of the data points), spending and savings data were reported separately for residential and non-residential efficiency investment; in 37 other cases, data were available only at the portfolio level. In aggregate, the data set

[2] If sector level information was not available for a given program administrator in a given year, portfolio level information was used instead.

represents approximately $25 billion of historical and planned investment (in 2011$), generating cumulative annual energy savings of over 105,000 GWh / yr.

Once the data were compiled, the programming language R was used in an iterative process to find a best fit multiple linear regression equation to detect and account for covariance between 2011$ / kWh-yr and different sets of explanatory variables.[3] The first regression captured the four variables by testing % Savings, Year, Maturity, Residential, Non-residential, Planned Spending and Savings, California, and New England. This regression had an adjusted R-squared of 0.368. The variables % Savings, California, and New England were all found to be statistically significant at the 99.9% confidence level; and Non-residential and Planned Spending and Savings at the 95% confidence level. The remaining terms had confidence levels below 90%.

The next step was to force the intercept to zero, since, in the absence of any energy efficiency activity, there should be no costs. This more than doubled the adjusted R-squared to 0.846, made Year and Maturity statistically significant with a confidence level above 99.9%, and improved the confidence level of Planned Spending and Savings to 99%. Since Residential was not significant at a confidence level of 90% or higher, it was dropped from the equation. Dropping Residential significantly increased the F-statistic, which rose from 325.7 to 372; it created only a slight impact on the adjusted R-squared, dropping it by 0.0001. The resulting regression had terms with confidence levels above 99% and an adjusted R-squared of 0.8459.

Next, various terms were added and removed from the estimated equation in attempts to improve the fit of the regression. Binary variables were used to replace the Year term (Yr_06_08 and Yr_09_11). Non-linear transformations[4] of % Savings, Year, and Maturity were also tested in combination with and as a replacement for the original temporal terms. This refinement process led to the addition of two nonlinear transformations of %_Savings, % Savings^{-1} (Per_Sav_Pow) and % Savings^{2} (Per_Sav_Sq), to the model.

Finally, the model still used the Year term, which was troubling since Year co-varies substantially with the Maturity term for a given administrator. Removing the Year variable degraded the fit of the model and the confidence levels of the other variables. It was found that the Maturity and Year portions of the function could be expressed in terms of Maturity and First Year, reflecting the first year of data in the data set for a given program administrator. While the two equations are functionally equivalent, First Year is believed to be a better variable because it stays constant for a given program administrator. The resulting best-fit model is shown in Figure 2**,** and its summary statistics are shown in Figure 3.

Figure 2. Best-Fit Multiple Linear Regression Model for 2011$ / kWh-yr

$$y = -25.209x_1 + 0.00008\frac{1}{x_1} + 522.727x_1^2 + 0.00017\,x_2 + 0.00745x_3 - 0.00788x_4 + 0.07219x_5 + 0.16896x_6 + 0.20259x_7$$

[3] R is a programming language and software environment for statistical computation language distributed under the GNU software license (http://www.r-project.org/about.html).

[4] The non-linear transformations used were $y=x^{-1}$, $y=x^2$, and $y=x^3$

Figure 3. Best-Fit Multiple Linar Regression Model Statistics

Variables		Coefficients	Std. Error	t value	Pr(>|t|)	Signf
Dol_kWh_Yr_2011	Y					
Intercept		0				
Per_Sav	X_1	(25.21)	3.05	(8.28)	1.3E-15	***
Per_Sav_Pow	$1/X_1$	0.00008	0.00002	5.13	4.3E-07	***
Per_Sav_Sq	X_1^2	522.73	86.24	6.06	2.8E-09	***
Yr_1	X_2	0.00017	0.00001	16.51	1.6E-48	***
Maturity	X_3	0.00745	0.00124	6.00	3.9E-09	***
Nonres	X_4	(0.08)	0.01	(7.23)	2.1E-12	***
Planned	X_5	0.072	0.015	4.88	1.5E-06	***
CA	X_6	0.169	0.021	7.97	1.2E-14	***
NE	X_7	0.203	0.014	14.94	1.7E-41	***

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1*

Regression Statistics		Residuals	
Residual standard error	0.1168 on 464 degrees of freedom	Min	-0.275
Multiple R-squared	0.8774	1Q	-0.070
Adjusted R-squared	0.875	Median	-0.010
F-statistic	368.8 on 9 and 464 DF	3Q	0.058
p-value	< 2.2e-16	Max	0.535

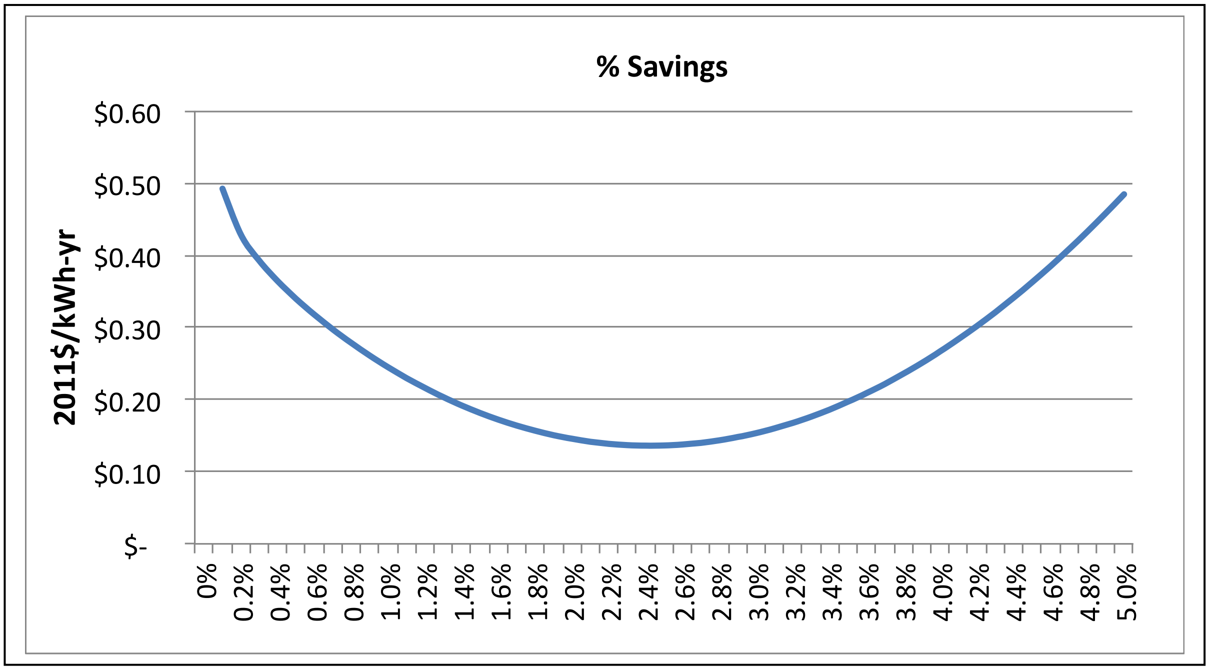
All the model's estimated coefficients have confidence levels beyond 99.9%, making them highly statistically significant. The model accounts for over 87% of the sample variance of the dependent variable, acquisition cost per kWh / yr. The model predicts that non-residential efficiency acquisition costs are \$0.08 / kWh-yr lower than residential or total portfolio costs. Acquisition costs are lower outside California and New England, with the former adding \$0.169 / kWh-yr and the latter adding \$0.203 / kWh-yr to predicted costs.

The model also predicts that acquisition costs increase with portfolio maturity. Each calendar year of maturity increases the marginal cost of energy, in 2011\$ / kWh-yr terms, by \$0.00745. The year in which the portfolio starts has much less impact on costs. An administrator would have to start more than 40 years earlier to offset the impact of one year of maturity.[5]

For the savings term, the model predicts acquisition costs as a polynomial function of savings depth. Figure 4 is a graph of the equation from Figure 2 for % Savings between 0 and 5%, with First Year set to 2009, Maturity set to 3, Planned Spending and Savings set to 1, and the rest of the variables set to 0.

[5] 0.00745 / 0.00017 ≈ 43.8

Figure 4. Graph of Percentage Savings Effect on Costs of Savings

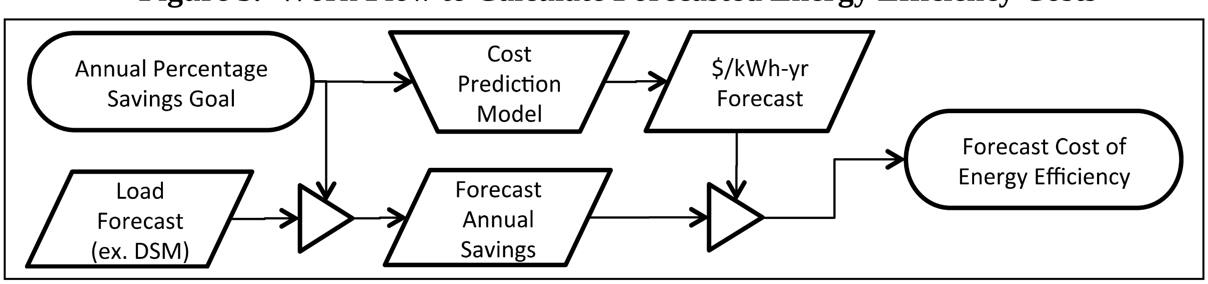


The 2011$ / kWh-yr falls as savings increase, until approximately 2.5%, at which point the downward pressure on costs begins to reverse. The rate of decline also slows as savings increase, until costs bottom out, after which the rate of cost increases also rises. This initial drop is clear evidence of economies of scale lasting well into the top tier of energy efficiency savings, at which point the rise in costs shows that diminishing returns predominate. Additional evidence of diminishing returns comes in the form of the positive coefficient for maturity; every year the portfolio matures, the cost of energy savings increases nearly $0.01.

Example of Forecasting Costs of an EERS

The GEEG model can be used to estimate the expected cost of future energy efficiency investment on the part of a hypothetical energy efficiency administrator. For this example, consider a jurisdiction outside New England and California. It is 2012, and this jurisdiction has just established an energy efficiency resource (EER) that sets a goal of saving 2% a year, starting in 2016 and going through 2020. Using the model, an administrator can estimate the jurisdiction's cost of achieving the goal set forth by the EER. Figure 5 outlines the steps to get to forecast costs for energy efficiency.

Figure 5. Work Flow to Calculate Forecasted Energy Efficiency Costs



The only other data required, besides the annual savings percentage goals, is a load forecast that excludes DSM. The target savings percentages applied to the three polynomial terms of the equation, along with other assumptions regarding the program administrator, return forecast costs per annual kWh. Next, the annual percentage savings are multiplied by the projected load to get the forecast of annual savings. Finally, the forecast cost of energy is applied to the forecast savings to get a total cost to the administrator for meeting the EERS' goals. Figure 6 presents the results for the administrator.

Figure 6. Example Calculations of EERS Costs

Assumptions		Year	Savings	2011$ / kWh-yr	Load Forecast (GWh)	Incremental Annual Savings (GWh)	Costs (Millions 2011$)
First Year	*2009*	2012	0.25%	$ 0.41	1,000	2.5	$ 1.02
Nonres	*0*	2013	0.50%	$ 0.35	1,018	5.1	$ 1.77
CA	*0*	2014	1.00%	$ 0.26	1,036	10.4	$ 2.69
NE	*0*	2015	1.50%	$ 0.20	1,055	15.8	$ 3.23
Planned	*1*	2016	2.00%	$ 0.18	1,074	21.5	$ 3.77
Initial Load (GWh)	*1,000*	2017	2.00%	$ 0.18	1,093	21.9	$ 4.00
Load Growth	*1.8%*	2018	2.00%	$ 0.19	1,113	22.3	$ 4.24
		2019	2.00%	$ 0.20	1,133	22.7	$ 4.48
		2020	2.00%	$ 0.21	1,153	23.1	$ 4.73

The administrator is assumed to start with a sales base of 1,000 GWh in 2012, and is projected to have load growth of 1.8%, going forward. Savings started at 0.25% in 2012, went to 0.5% in 2013, 1% in 2014, and 1.5% in 2015, before reaching 2% in 2016 and beyond. Cost per annual kWh started at $0.41, before dropping by more than half to $0.18 in 2016, and then began to creep up to $0.21 by the end of the analysis period. Although costs per unit savings went down, the total cost to the administrator continued to grow as the magnitude of savings continued to grow.

Limitations, Future Research, and Additional Applications

The primary limitation of the model is that it applies only to program administrator investment costs of energy efficiency resources. It does not include the costs participating customers contribute toward efficiency resource acquisition; nor does it include cost savings that participants experience. The cost savings to participants include lower operation, maintenance, and replacement costs associated with high-efficiency equipment, which often has much longer life expectancies than standard equipment. Efficiency program administrators do not widely or consistently report information on customer costs and cost savings. Any attempt to forecast total resource costs of efficiency investments will need to estimate the net participant costs that would be associated with the program administrator costs predicted by the model presented here.

Another limitation worth highlighting is variability in the reliability of the reported savings data. Some jurisdictions such as Vermont and California are subject to rigorous measurement and verification procedures; other jurisdictions have less-stringent procedures. Uniform standards of reporting would also reduce the time and error in deriving usable data on costs and savings, particularly by customer sector.

Improving the model means, first and foremost, expanding the data set. As time passes, energy efficiency investment continues to grow, future plans change, and new data become available. The US EIA has released 2010 data from Form EIA-861, and program administrator regulatory reports on activity from 2011 will begin to trickle in over the next few months. In addition, planned spending and savings fluctuate widely, and the data will frequently need to be updated to stay current.

Another way in which the data could be improved is in the characterization of the first year of portfolio operation. For a portion of administrators, the First Year data does not correspond with the first year in which they began pursuing energy efficiency, but instead with the first year that data was added to the collection. Fixing this could lead to improvements in the descriptive power of the model. The effort required to collect, analyze, clean, and document the continuous stream of information is substantial. The rate and quality of data collection could be improved through more open collaboration among regulated jurisdictions with investments in energy efficiency.

Although the model is statistically robust, the forecast error is necessarily higher, the further out-of-sample it is used to predict costs. Additional high-performance portfolio experience information is needed to narrow the confidence interval around costs associated with top-tier savings performance (that is, portfolios achieving annual energy savings of 2% of electricity sales and above). Future analysis will estimate the forecast standard error so that users can calculate a confidence band around the predicted costs.

The authors have identified several areas in which the model might be enhanced. One concern is the evidence of residual serial autocorrelation (discussed in the Appendix). Other potential areas of exploration include: (1) testing interaction terms combining continuous explanatory variables (such as maturity) with dichotomous variables (such as region); (2) further manipulating the data using power transforms of variables[6]; and (3) examining non-linear regression models such as logarithmic formulations (for example, single-log or log-log specifications).

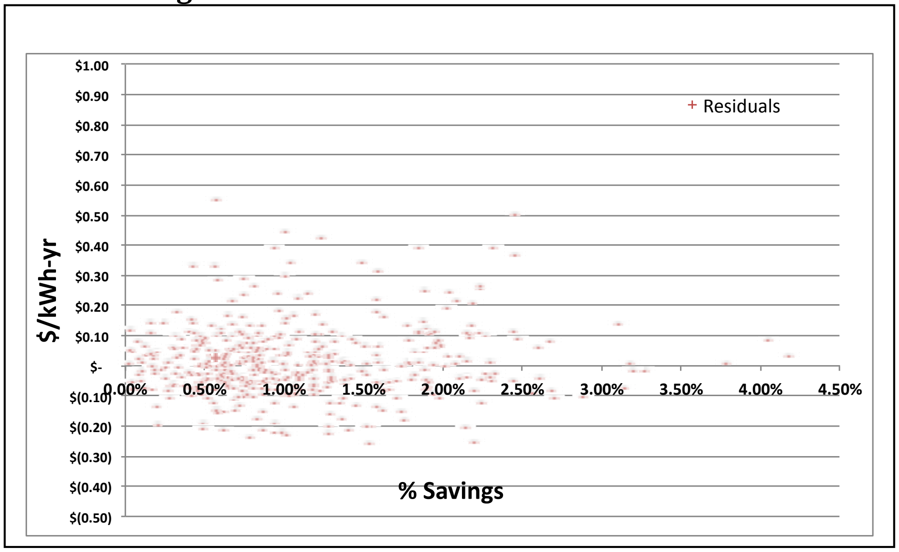
Ultimately, the model described in this paper has many applications beyond the simple example presented here. It could be used as a benchmarking tool for administrators, or as a way to evaluate past results. The binary variables and residual values can be used to establish cost ranges for sensitivity analysis. Forecast unit costs can be combined with lifetimes to derive a cost of energy efficiency comparable to supply costs, something that is extremely important for evaluating DSM in the context of long-term resource planning. These are just a few of the ways in which an understanding of the complex relationship between energy efficiency spending, savings, time, customer sector, and location can benefit anyone involved in the business of energy efficiency resource acquisition planning, management, or oversight.

Appendix: Serial Residual Autocorrelation

Another important way to analyze the regression is by examining its residual errors, or the differences between the values predicted by the model and the actual values in the data set used to find the linear regression. Figure 7 maps the residual errors for the model against % Savings and shows that the spread of errors stays relatively consistent for different savings levels, with the largest residual errors overestimating costs.

[6] Power transforms (such as the Box-Cox transformation) are power functions (such as $y=x^2$) that can be applied to data so that rank is preserved and variance may be stabilized (making the data more normally distributed).

Figure 7. Residual Errors of Best-Fit Model



Finally, The Durbin-Watson (D-W) statistic is a way to test for the presence of autocorrelation in the residuals of a regression. Autocorrelation is not desirable because it indicates that there might be dependencies between parameters in the model, which can bias estimated coefficients and their standard errors. The D-W statistic lies between 0 and 4, with a value of 2 indicating no autocorrelation, a value greater than 2 indicating negative correlation, and a value less than 2 indicating positive autocorrelation (Draper & Smith, 1998). Since the Durbin-Watson Statistic requires an ordered data set, the test was run for the regression using the data set ordered by each variable in the data set. The summary of the test results that had p-values below 1% (that is, a 99% confidence level) is shown in Table 2.

Table 2. Summary of Durbin-Watson Statistics for Regression[7]

Minimum	Maximum	Median	Mean
0.81	1.66	1.29	1.33

Usually, the Durbin-Watson test is used on regressions of time series data. The test results for the data set ordered by the Year and Maturity variables, the two time series variables in equation, were approximately 1.5, higher than the median and mean values. In general, these results indicate some evidence of serial autocorrelation, and one of the goals of future research should be to find some way to get the values of the Durbin-Watson statistic closer to 2.

References

Achim Zeileis, and Torsten Hothorn. 2002. *Diagnostic Checking in Regression Relationships. R News 2(3), 7-10*. URL http://CRAN.R-project.org/doc/Rnews/

Draper, Norman R., and Harry Smith. 1998. *Applied Regression Analysis, Volume 1 (3rd Ed.)*. John Wiley & Sons. Pages 179-205

[7] The function *dwtest* in the package *lmtest* was used for performing the calculations (Achim & Hothorn 2002).

[GEEG] Green Energy Economics Group, Inc. 2011. *Electric Energy Efficiency Resource Acquisition Options for Nevada Power Company d/b/a NV Energy*. Sierra Club Nevada.

Nowak, S., M. Kushler, M. Sciortino, D. York, and P. Witte. 2011. *Energy Efficiency Resource Standards: State and Utility Strategies for Higher Energy Savings*. Washington, D.C.: American Council for an Energy-Efficient Economy.

[R] R Development Core Team. 2011. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. URL http://www.r-project.org/.

Sciortino, M., S. Nowak, P. Witte, D. York, and M. Kushler. 2011. *Energy Efficiency Resource Standards: A Progress Report on State Experience*. Washington, D.C.: American Council for an Energy-Efficient Economy.

Sciortino, M., M Neubauer, S. Vaidyanathan, A. Chittum, S. Hayes, S. Nowak, and M. Molina. 2011. *The 2011 State Energy Efficiency Scorecard*. Washington, D.C.: American Council For an Energy-Efficient Economy.

[US EIA] U.S. Energy Information Administration. 2011. *Summary Electricity Statistics 1999-2010*. Data from Electric Power Annual 2010 Release Date: November 9, 2011. URL http://www.eia.gov/electricity/data.cfm#summary

U.S. House of Representatives. 2007. *Energy Independence and Security Act of 2007*. 110th Congress, first session. HR 6. Washington, D.C.: General Printing Office.