Tangled: Isolating SEM Savings

Andrew Stryker, Siyu Wu, Julia Vetromile, DNV GL

ABSTRACT

Energy efficiency program sponsors in many jurisdictions have launched efforts to capture energy savings arising from strategic energy management (SEM) programs. SEM is an approach that aims to change the mindset of management and strategically manage energy costs as a controllable expense. Through a combination of training, technical support, and development of peer networks, these programs encourage the owners and operators of industrial plants to adopt continuous improvement techniques in energy management. Though SEM programs focus on changing operational practices, they may also encourage participants to undertake retrofit and capital improvements supported by other programs.

One of the principal challenges in evaluating SEM-type programs is to disaggregate energy savings attributable to behavioral and management changes directly supported by the program from savings associated with installation of retrofit and capital measures. This task is complicated by changes in production volumes or types of products processed in the facility, both of which have a large effect on energy consumption. Therefore, methods to account for capital improvements and changes in production activity are critical to assessing savings attributable to SEM programs.

This paper shows how to use regression techniques to separate the effects of more efficient operations from those of equipment changes, allowing evaluators to model how plant production, environmental effects, and detailed knowledge of how efficiency measures interact (or do not interact) with production result in energy savings. The method accounts for seasonal variation in product type and raw material inputs as well as allowing evaluators to simultaneously estimate realization rates to energy measures and capture savings due to behavioral changes. The paper presents the results of using this method for the evaluation of SEM at food-processing plants for the Northwest Energy Efficiency Alliance (NEEA).

Introduction

NEEA has been implementing an Industrial Initiative that aims to transform the market for industrial energy management and to promote SEM practices since 2005. The initiative is currently focused on the food-processing industry and encourages facilities to incorporate continuous energy improvement through SEM practices in their operations. Estimation of SEM energy savings provides NEEA with direct feedback of the program impact to better inform policy makers. DNV GL estimated energy savings for this program for 2012 and 2013.

SEM programs promote two types of activities: (1) behavioral and operational optimization measures or actions (BEM) and (2) capital, retrofit, and maintenance improvements (EEM). In practice, energy savings due to BEM and EEM occur simultaneously and contribute to the overall SEM energy savings in a "tangled" fashion. While most EEM savings can be evaluated by bottom-up field measurement of key performance parameters using Option A of the International Performance Measurement and Verification Protocol (NREL 2002; DOE 2008), BEM savings are challenging to quantify directly by measurement. It is either costly or impractical to establish effective control groups for behavioral changes for industrial sites with ongoing production targets to meet (LBNL 2012; DOE 2014).

To address this challenge, DNV GL (formerly DNV KEMA) developed a regression-based method for the evaluation of the 2013 NEEA Industrial Initiative energy savings. This method adopts a top-down modeling approach, quantifies the overall SEM energy savings, and disaggregates them into those attributed to BEM and EEM. This involves recovering two hypothetical scenarios using bottom-up, field-validated EEM savings: (1) that only EEM is implemented and (2) neither EEM or BEM are implemented. By modeling energy consumption of these two scenarios and examining their differences, we isolate BEM savings from overall SEM savings.

We estimated BEM and EEM savings for 10 food-processing facilities that are actively engaged in a SEM program throughout 2013. These facilities are from multiple firms and located across three states under various climate zones. A total of 25 EEM measures were verified and validated. The top-down models demonstrated excellent goodness-of-fit (GOF) in all but one instance, and appear to capture the underlying system dynamics of nine out of 10 involved facilities. Furthermore, the estimated savings are consistent with the end-use energy efficiency records of the facilities. Consequently, the estimated savings obtained by the regression method demonstrate both statistical and practical significance.

The next section presents the modeling approach and data pre-processing, followed by results and conclusions.

Modeling Approach

Data Source

The 10 facilities participating in NEEA's food processing initiative are located in three states in the Pacific Northwest: Oregon, Idaho, and Washington. Through their contractor, NEEA collected the monthly energy consumption (electricity and gas) and net production data for each facility for the entire length of time it participated in SEM programs. The contractor also collected data on specific EEMs and associated bottom-up savings for each facility since its involvement in the program.

For the weather data, we used meteorological readings from the nearest possible National Oceanic and Atmospheric Administration (NOAA) weather station for each facility. The original NOAA weather data included dry bulb, wet bulb, and dew point temperatures and relative humidity on an hourly interval. We verified the original weather data by checking temperature range and seasonal patterns. The temperature range is consistent with climate in the Pacific Northwest region where there are typically few readings above 100°F or below freezing.

To resolve the difference between hourly weather data and monthly energy consumption data, we calculated monthly heating degree days (HDD) and cooling degree days (CDD) for each facility. Degree days measure the amount of time during the month a facility is below or above a reference or basis temperature. This reference temperature is usually 65°F (Ristinen and Kraushaar 2006). When the outside temperature is above (below) 65°F, buildings spend energy cooling (heating). Cooling and heating degree days are the cumulative time over the month that the building is above and below, respectively, the reference temperature. In this analysis, we computed HDD and CDD for an average reference temperature, 65°F.

Historical datasets of energy consumption, production, bottom-up EEM savings, and weather data serve as the data source for our top-down analysis.

Top-Down Model

The top-down model uses linear regression techniques to predict changes in electric and gas consumption as functions of non-program factors such as weather and production volume. According to previous studies on the same facilities, energy consumption of different production activities demonstrates different degrees of dependency on weather-related factors (DNV KEMA 2014; ERS 2012; Cadmus 2011). We tested two top-down model specifications to address this fact.

The first model, referred to as the P model, includes only production as the independent variable. The second model, called the PHC model, adds HDD and CDD as two extra independent variables. We evaluated and selected the most relevant model for each facility to produce more rigorous savings estimates.

Disaggregation Strategy

The biggest challenge of the top-down analysis is to disaggregate energy savings in terms of BEM and EEM actions. Savings estimates from energy consumption (billing) data reflect only the overall effect of both BEM and EEM activities. An analogy would be measuring a car's total reduced fuel consumption after both improving driving behavior (BEM measure) and upgrading with an energy-efficient component, such as a diesel engine (EEM measure), and then trying to estimate how much fuel savings were attributable to each measure. It would not be possible to determine without consumption data for when (a) only driving behavior is improved or (b) only the energy-efficient component is upgraded.

However, in this scenario, if the diesel engine manufacturer provides annual estimated savings for replacement (EEM measure) and these savings are subtracted from the total end-use consumption savings, it is possible to determine approximate savings based on driving behavior alone (BEM measure).

In our analysis, we applied a similar strategy to recover the energy consumption trend for only the BEM activities by using energy consumption data in both the reference period and 2013 to estimate savings that occurred in 2013.

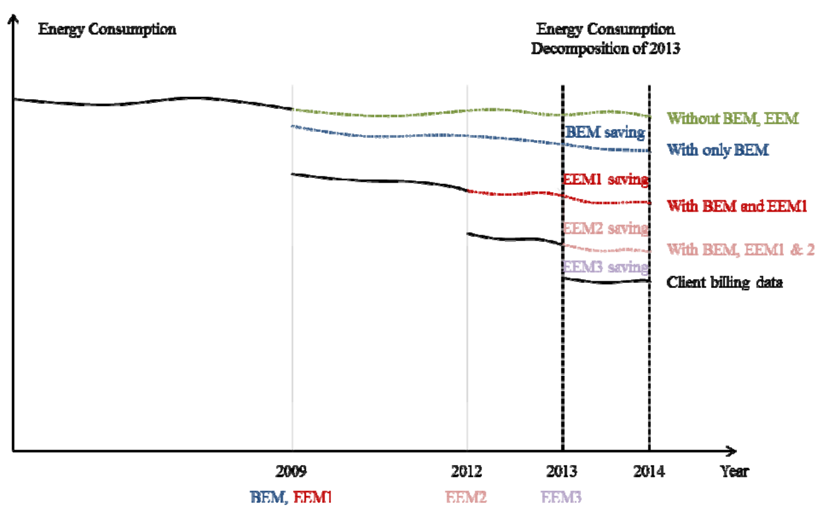

Figure 1. Facility energy consumption trends under different scenarios.

Figure 1 illustrates energy consumption trends for an example facility. It engaged in NEEA's industrial initiative for SEM (including both BEM and EEM) starting in 2009. Between 2009 and 2013, the facility implemented EEMs. We grouped projects by when they were completed in three phases: 2009-2011 (EEM1), 2012 (EEM2), and 2013 (EEM3). The solid line in black represents the energy consumption (billing) data that are directly available. The dashed lines in green, blue, and red represent recovered trends under three reference scenarios. For example, the blue dashed line recovers what energy consumption would be if only the BEM actions had been implemented. The red dashed line recovers what consumption would be if only the BEM actions and EEM1 had been implemented.

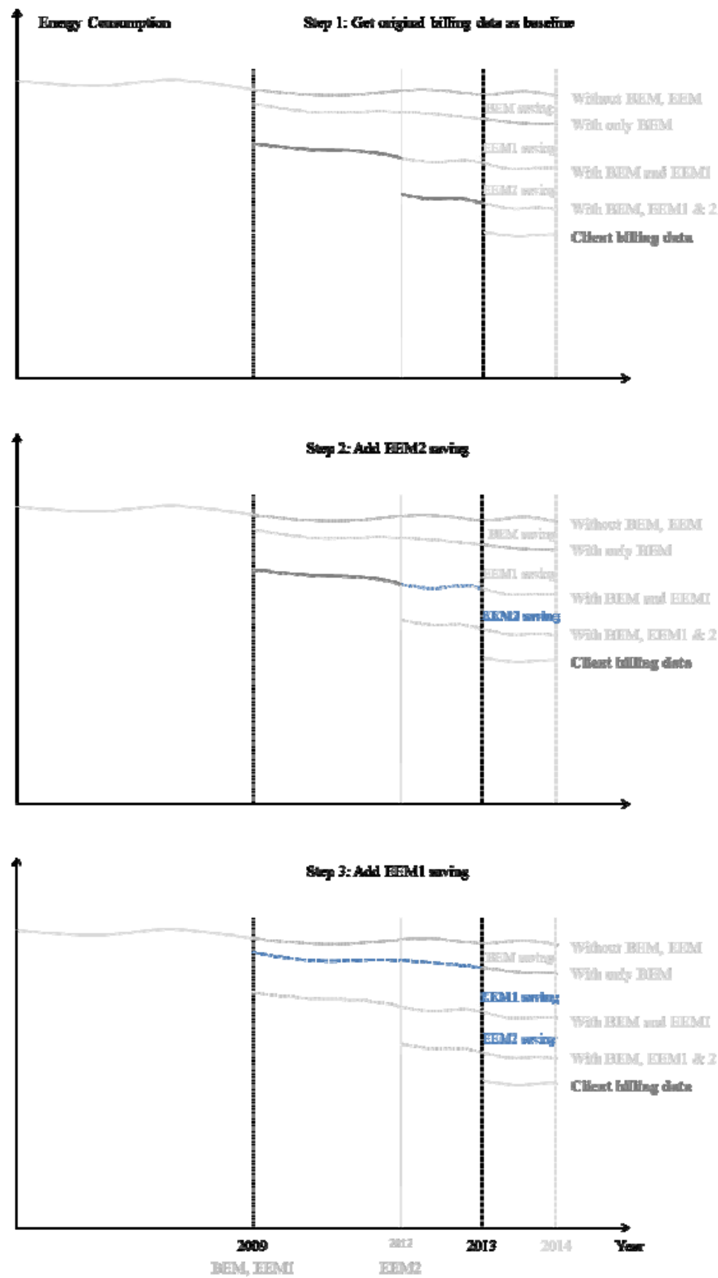

Figure 2. Recovered consumption trend of the scenario when only BEM was implemented

Next, the question is how to recover the green and blue dash lines based on the consumption data and the bottom-up estimated savings.

Figure 2 illustrates the procedures for recovering the blue dashed line (only BEM activity) by allocating bottom-up savings. In the top subplot, end-use consumption data (gray solid lines) are used as the baseline. During 2012, we add the bottom-up EEM2 saving on top of the baseline. This recovers the energy consumption trend (blue dashed line in the middle subplot) if only the BEM and EEM1 actions are implemented. To distinguish the effect by the EEM1 program, we add the estimated EEM1 savings to each year from 2009 to 2013, because measures implemented in 2009 are expected to persist into 2013. Eventually, we obtain the needed trend (blue dashed line) in the bottom subplot that represents the trend when only the BEM actions are implemented.

With the recovered energy consumption trend, and production and weather data during the same period time, we conduct a regression to obtain the coefficients of the top-down model. Eventually, we use the resultant model to predict energy consumption in 2013.

Thus far, we have demonstrated how to recover BEM savings. In the following paragraphs we will describe how to recover the green dashed line, which is the scenario that no BEM and EEM actions had been implemented at all. We start with the facility energy consumption one year prior to SEM activity. SEM was considered to be effective when the facility achieved the sustaining level as defined by NEEA. This energy consumption serves as the reference for evaluating the consumption change in 2013. Take the facility in Figure 3 as an example. The SEM activity became fully effective in 2009. Energy consumption in 2008 (green solid line in the top subplot) becomes the reference.

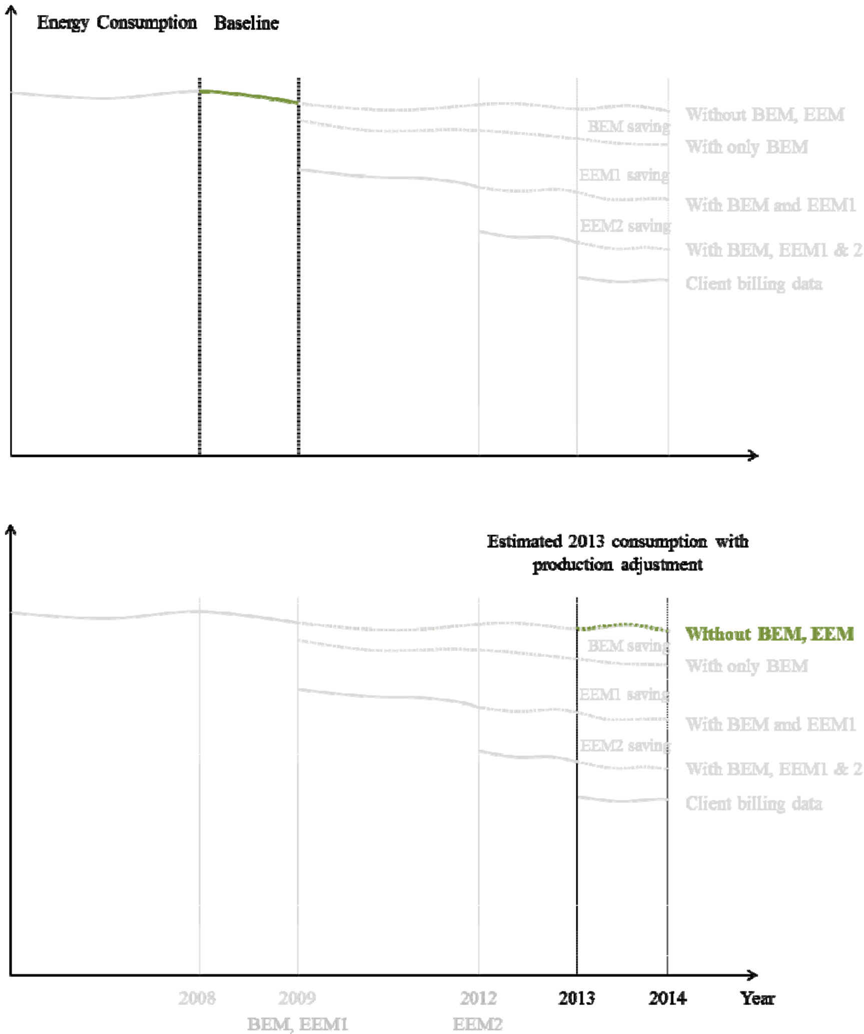

Figure 3. Recovered consumption trend of the scenario without any programs.

To compensate for the production difference between the reference year and evaluation year, we adjust the reference year's energy consumption (E_{ref}) by the production ratio between the evaluation (P_{eval}) and reference (P_{ref}) year. This adjusted consumption (the green dashed line in the bottom subplot) becomes the final baseline in the evaluation year ($E_{baseline}$) for calculating the savings. Mathematically,

$$E_{baseline} = E_{ref} \cdot \frac{P_{eval}}{P_{ref}}.$$

To this end, we have recovered all consumption trends needed for estimating the energy savings due to BEM activities.

Model Specification

By examining the original time series of production and energy consumption, we identified a strong linear relationship between them. Figure 4 demonstrates such observations between total energy consumption and production for all 10 facilities.

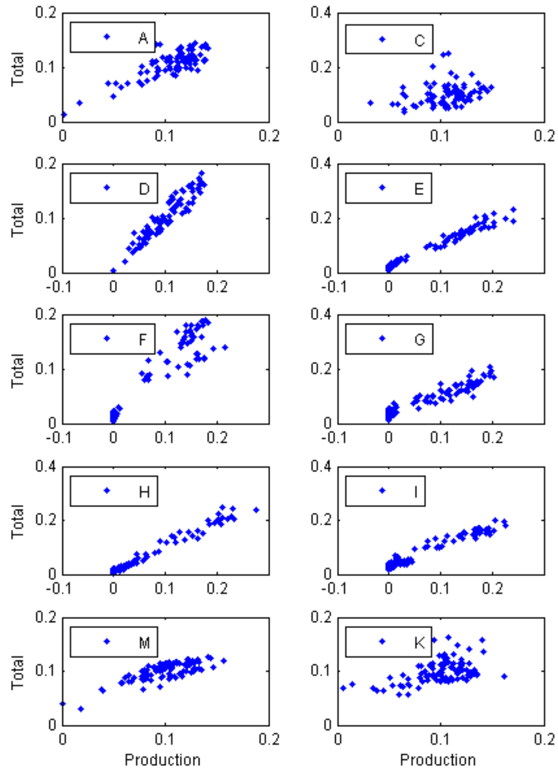

Figure 4. Scatter plots of normalized production and total energy consumption for each of the 10 involved facilities.

In previous evaluation of similar facilities located in the same region, local temperatures were found to influence energy consumption to a limited, but measureable, extent. Therefore, we tested two top-down models with different sets of independent variables: (1) the production (P) only model (P model) and (2) the production, HDD, and CDD model (PHC model). For both models, the dependent variable, energy consumption (E), is represented as linear combinations of independent variables. Mathematically, P model:

$$E_t = a \cdot P_t + b_t + \varepsilon_t,$$

PHC model:

$$E_t = c \cdot P_t + d \cdot HDD_t + e \cdot CDD_t + f_t + \varepsilon_t,$$

where a, c, d, and e are regression coefficients, b, f are intercepts, ε is the residual, and t is the time index.

Modeling Results

Production Model with and without Weather Effects

Both the P and PHC models demonstrated excellent accuracy in tracking energy consumption for all involved facilities. The average correlation coefficient between fitted values and observed measurements is above 0.90. Given the uncertainties of data collection, and the relatively low data resolution, this is a relatively high GOF result. Figure 5 shows gas-modeling results from both models for one example facility. Other facilities and electricity modeling demonstrated similarly good results.

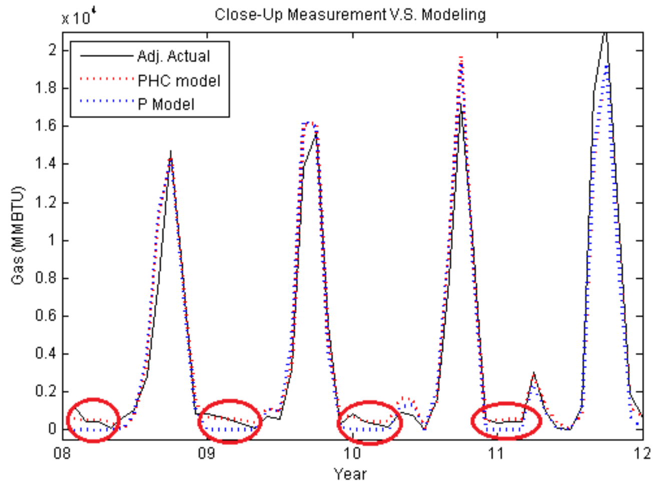

Figure 5. Comparison of gas modeling produced by P model and PHC model.

While both models tracked peak energy consumption (typically June to November) fairly well, the PHC model outperformed the P model in capturing the base loads circled in red in Figure 5. This is especially true when the production is zero. The extra HDD and CDD information enhance the top-down model's ability to recover the fact that minimal energy consumption exists, even when there is no production.

The Disaggregation Strategy

Modeling results show that the disaggregation strategy to allocate bottom-up savings is a success. Modeling GOF of all facilities demonstrated an increase in the Pearson correlation coefficient (r) and a decrease in mean squared error (MSE) with the strategy implemented. Consider the example of electricity modeling in Facility K as shown in Figure 6, which compares the results when the disaggregation strategy is (and is not) implemented. The correlation coefficient increased significantly from 0.75 to 0.94 when bottom-up savings are included in the model. Similar results have been observed for gas modeling.

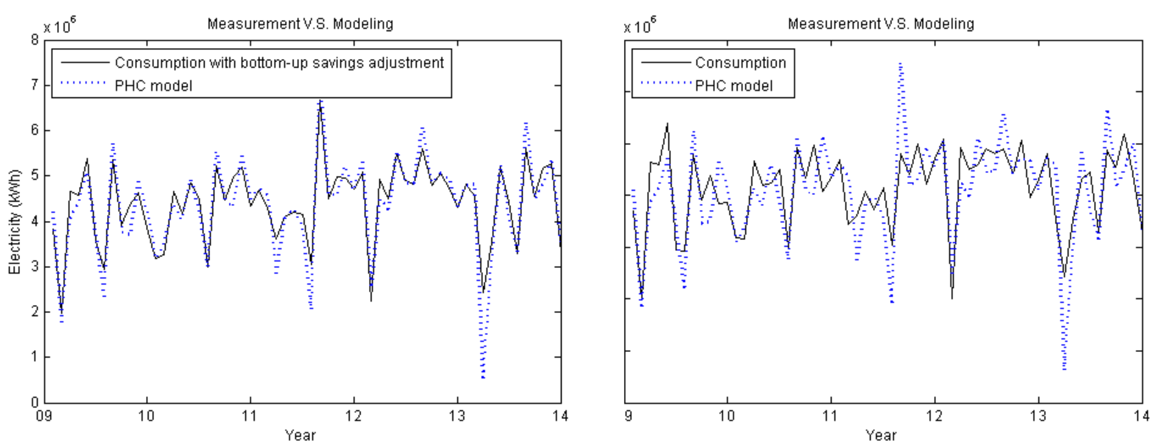

Figure 6. Modeling of electricity consumption with (left) and without (right) the disaggregation strategy.

The correlation coefficient improvements for all facilities are shown in Figure 7. For both electricity modeling and gas modeling, the correlation coefficient increased by 5.23%. On the other hand, Table 1 takes the PHC model as an example and shows that at the same time the mean squared error decreased by 63.24%.

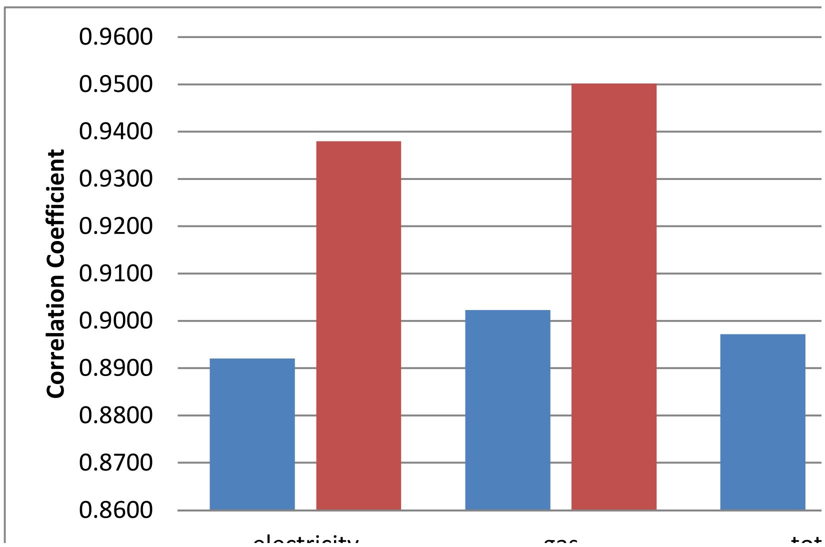

Figure 7. Correlation coefficient comparison with and without the disaggregation strategy.

The mean squared error measures the overall fit (Schunn and Wallach 2005). In our modeling, this measure represents the exact deviation of modeling from the actual energy consumption, and hence it relates directly to the estimated energy savings. Consequently, a 63% reduction in the mean squared error significantly increases the accuracy of our estimated energy savings.

Overall GOF

With HDD and CDD as additional independent variables and the disaggregation strategy, the top-down model demonstrated excellent GOF results for both gas and electricity modeling. Table 1 lists the complete results of correlation coefficients for all facilities involved. The average correlation coefficients for electricity and gas modeling are 0.93 and 0.95 respectively, excluding Facility C. These excellent GOF results empirically suggest that the top-down model is able to capture system dynamics of energy consumption accurately.

Therefore, the estimated savings produced by the top-down model are of statistical significance.

Table 1. Goodness-of-fits of the top-down models.

Site	Source	Without Disaggregation r	With Disaggregation r

Site	Source	Without Disaggregation r	With Disaggregation r
A	electricity	0.846	0.8792
	gas	0.9184	0.9365
	average	0.8822	0.9079
C	electricity	0.4816	0.6909
	gas	0.9184	0.9216
	average	0.7	0.8063
D	electricity	0.8146	0.8146
	gas	0.9391	0.9419
	average	0.8769	0.8783
E	electricity	0.9641	0.9767
	gas	0.9817	0.9817
	average	0.9729	0.9792
F	electricity	0.9843	0.9859
	gas	0.9144	0.9144
	average	0.9494	0.9502
G	electricity	0.9633	0.9649
	gas	0.9508	0.9508
	average	0.9571	0.9579
H	electricity	0.9363	0.9427
	gas	0.9819	0.9898
	average	0.9591	0.9663
I	electricity	0.969	0.974
	gas	0.9714	0.9723
	average	0.9702	0.9732
K	electricity	0.7592	0.9464
	gas	0.6285	0.8993
	average	0.6939	0.9229
M	electricity	0.7914	0.9573
	gas	0.8344	0.965
	average	0.8129	0.9612
Overall	electricity	0.851	0.9133
	gas	0.9039	0.9473
	average	0.8774	0.9303
Excluding C	electricity	0.892	0.938
	gas	0.9023	0.9502
	average	0.8972	0.9441

It should be noted that the GOF results of facility C were poor with an average correlation coefficient being below 0.75, thus we were not able to fit a statistically significant model to its data. The poor fit of the electric model likely reflects that factors other than production and weather drive energy consumption. The regression used data between 2010 and 2012 to fit the model. During interviews, plant staff noted operational and raw material problems that resulted in higher energy consumption. The gas consumption results for 2013 reflect fuel switching from natural gas to wood. Because the modeling process does not account for fuel switching and the electric model had poor fit, we excluded facility C in the final summaries.

Conclusions

We developed a top-down modeling strategy to quantify and deconstruct changes in energy consumption for 10 NEEA facilities involved in NEEA's Industrial Initiative. In our approach, monthly production and weather data were used as independent variables and a regression-based strategy that uses bottom-up savings to deconstruct total savings into BEM and EEM activities was applied. This method captured the underlying system dynamics accurately and demonstrated excellent GOF results with an average correlation coefficient above 0.94.

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