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Estimating Industrial Building Energy Savings using Inverse Simulation

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ABSTRACT

Estimating energy savings from retrofitting existing building systems is traditionally a time intensive process, accomplished by developing a detailed building simulation model, running the model with actual weather data, calibrating the model to actual energy use data, modifying the model to include the proposed changes, then running the base and proposed models with typical weather data to estimate typical energy savings.

This paper describes a less time-intensive method of estimating energy savings in industrial buildings using actual monthly energy consumption and weather data. The method begins by developing a multivariate three-parameter change-point regression model of facility energy use. Next, the change in model parameters is estimated to reflect the proposed energy saving measure. Energy savings are then estimated as the difference between the base and proposed models driven with typical weather data. Use of this method eliminates the need for estimating building parameters, system performance, and operating practices since they are included in the inverse simulation model. It also eliminates the need for model calibration since the inverse model is derived from actual energy use data.

The paper describes the development of statistical inverse energy signature models and how to modify the models to estimate savings. Expected savings from inverse simulation are compared to savings predicted by detailed hourly simulation, and sources of error are discussed. Finally, the method is demonstrated in a case study example from the industrial sector. Limitations of the approach for complex building systems and the uncertainty of estimated savings are discussed.

INTRODUCTION

Estimating energy savings from retrofitting existing building systems is traditionally a time intensive process, accomplished by developing a detailed building simulation model, running the model with actual weather data, calibrating the model to actual energy use data, modifying the model to include the proposed changes, then running the base and proposed models with typical weather data to estimate typical energy savings. Moreover, the development of the detailed simulation model requires many assumptions about building parameters, system performance, and operating practices. The unavoidable calibration error and the assumptions required to simulate energy use introduce uncertainty into the process.

This paper describes an inverse simulation method of estimating energy savings in industrial buildings using actual monthly energy consumption and weather data. The method begins by developing a multivariate three-parameter change-point regression model of facility energy use. Next, the change in model parameters is estimated to reflect the proposed energy saving measure. Energy savings are then estimated as the difference between the base and proposed models driven with typical weather data. Use of this method eliminates the need for estimating building parameters, system performance, and operating practices since they are included in the inverse simulation model. It also eliminates the need for model calibration since the inverse model is derived from actual energy use data. This inverse simulation approach is appropriate for simple buildings, without simultaneous heating and cooling, and buildings that can be modeled as single zone buildings, such as many industrial facilities.

In the sections that follow, development of the statistical inverse energy signature models and how to modify the

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models to estimate savings are discussed. Next, expected savings from inverse simulation are compared to savings predicted by detailed hourly simulation, and sources of error are discussed. Finally, the method is applied to a case study example from the industrial sector. Limitations of the approach for complex building systems and the uncertainty of estimated savings are discussed.

OVERVIEW OF THE METHOD

The method of regressing utility billing data against weather data used here builds upon the PRInceton Scorekeeping Method, PRISM, which regresses building energy use versus variable-base degree-days (Fels, 1986a). However, the method described here uses temperature change-point models instead of degree-day models and can include other independent variables such as production.

Temperature change-point models were described by Kissock et al. (1998) and Kissock et al., (2003). The temperature change-point model method was extended to include additional independent variables by Kissock et al. (2003) and Haberl et al. (2003). The interpretation of regression coefficients, builds on early work by Goldberg and Fels (1986), Rabl (1988), Rabl et al. (1992) and Reddy (1989). Principle differences between this work and the aforementioned papers are that this work seeks to use inverse modeling proactively to estimate energy savings from retrofitting industrial building systems rather than retroactively to measure energy savings.

The method of estimating building energy savings using inverse simulation is accomplished in three steps. The first step is to develop a statistical multivariate three-parameter model of building energy use as a function of outdoor air temperature and production. Because this model describes the specific energy use pattern of a facility, it is called an “energy signature” model. The second step is to modify the energy signature model to simulate the performance of the building with the proposed energy efficiency measures. This model is formed by calculating the change in model coefficients to reflect the proposed energy saving measures. The third step is to drive both the base and proposed models with typical weather data to estimate the normalized annual consumption (NAC). This step can be accomplished using TMY2 (NREL, 1995) weather data, cooling degree hours (CDH) and heating degree hours (HDH), or binned temperature data. Typical energy savings are then calculated as the difference between the proposed model’s NAC and the baseline model’s NAC. The typical energy savings are needed to evaluate the economic feasibility of the proposed energy saving measures.

Description of Data and Software

The method described here is demonstrated using monthly utility bills for energy consumption data because of their wide availability and accuracy. However, the method can be used with higher time resolution data if they are available. When using utility billing data, the first step is to normalize the data to remove the effect of unequal days in the billing periods.

The method uses both actual and typical weather data. Kissock (1999) posts actual average daily temperatures for 157 U.S. and 167 international cities from January 1, 1995 to present on the internet. Typical weather is derived from TMY2 (or TMY3) data files from the National Renewable Energy Laboratory (NREL 1995). When using utility billing data, the average temperature during each billing period is calculated from the available temperature data The algorithms used to generate multi-variable change point models have been incorporated into the software designed for energy analysis (Kissock 2005), and the inverse simulations were performed using software for estimate energy savings (Sever and Kissock 2009).

Step 1: Energy Signature Models

The first step is to derive a statistical energy signature model of a facility’s electricity or fuel use as a function of the actual outdoor air temperature over the same time period. The weather dependence of energy consumption can accurately be described by three-parameter change-point models for most industrial facilities. Typical three-parameter heating (3PH) and three-parameter cooling (3PC) change-point models are shown in Figure 1. In the following discussion it is assumed that fuel is used for space heating and electricity is used for space cooling. Electricity or fuel consumption is graphed on the vertical axis versus outdoor air temperature on the horizontal axis. The coefficients of a 3PC model are the weather-independent electricity use (E_i), the cooling change-point temperature ($T_{b,C}$), and the cooling slope (CS). The coefficients of a 3PH model are the weather-independent fuel use (F_i), the heating change-point temperature ($T_{b,H}$), and the heating slope (HS). In facilities using the same energy source for both heating during winter and cooling during summer, a five-parameter model with both heating and cooling slopes can be developed (Haberl et al. 2003; Kissock et al. 1998; Kissock et al. 2003).

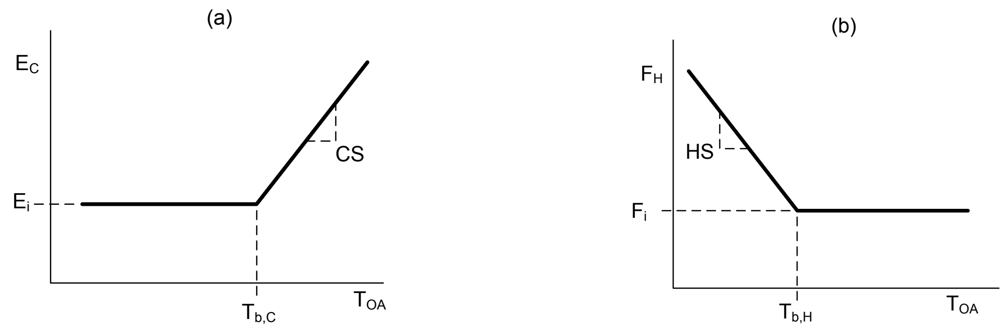


Figure 1 *(a) 3PC (Cooling) and (b) 3PH (Heating) regression models*

When electricity or the fuel is used in a production process in the facility, this method can be extended to include energy which is dependent on the amount of production by adding another regression coefficient. This will further refine the results of the regression, increasing the accuracy of the disaggregation of weather-independent and weather dependent energy use. The production coefficient, (PD), represents the response of electricity or fuel use with regards to the amount of production (P).

Using these models, electricity consumption can be estimated as a function of outdoor air temperature (T_{OA}) and production level, using Equation 1. Similarly, fuel consumption can be estimated as a function of outdoor air temperature (T_{OA}) and production level, using Equation 2. The superscript $^+$ denotes that the parenthetic quantity equals zero when it evaluates to a negative value.

$$E = E_i + CS \cdot (T_{OA} - T_{b,C})^+ + PD \cdot P \qquad (1)$$

$$F = F_i + HS \cdot (T_{b,H} - T_{OA})^+ + PD \cdot P \qquad (2)$$

Application of Model Coefficients to Building Systems

One of the strengths of this method is that the model coefficients directly characterize the physical properties of the envelope and operation of the facility. This eliminates the uncertainty associated with estimating the building parameters while calibrating a forward simulation model.

E_i and F_i represent the electricity and fuel use that is not related to weather or production. For example, in industrial facilities, lighting electricity use may be unrelated to weather or production. Similarly, fuel use to make up heat lost through the shells of furnaces and ovens is often unrelated to weather or production. (Eger and Kissock 2007) have developed a lean energy analysis method that targets these types of energy use for reduction.

CS and HS represent the variation of energy consumption with outdoor air temperatures. CS and HS include the building cooling and heating loads and the cooling and heating system efficiencies. In simple industrial buildings, the sum of conductive heat gain/loss through the building envelope and sensible heat gain due to ventilation and infiltration air dominate the cooling and heating loads of the building. Solar and latent cooling loads have been shown to be linearly related to outdoor air temperature (Ruch et al. 1993; Reddy et al. 1998), and are accounted for in these coefficients. Thus, the cooling and heating coefficients of the building, CC and HC, are given in equations 3 and 4 respectively. Where U is the overall building envelope conductance, A is the envelope area, V is the sum of ventilation and infiltration flow rate, ρ is the density of air and c_p is the specific heat of air. CS and HS, are the quotients of the external cooling and heating coefficients and the overall efficiency of the space cooling or heating system efficiency, η_C or η_H. The balance-point temperature, T_b is defined as the temperature above or below which space conditioning begins. T_b is a function of the thermostat set-point temperature, T_{set}, the sum of the internal loads from electricity use, solar gain and occupants, Q_i, and the CC and HC.

$$CC = UA + V\rho c_p \quad (3) \qquad HC = UA + V\rho c_p \quad (4)$$

$$CS = \frac{CC}{\eta_C} \quad (5) \qquad HS = \frac{HC}{\eta_H} \quad (6)$$

$$T_{b,C} = \mathrm{T_{set}} - \frac{\mathrm{Q_i}}{\mathrm{CC}} \quad (7) \qquad T_{b,H} = \mathrm{T_{set}} - \frac{\mathrm{Q_i}}{\mathrm{HC}} \quad (8)$$

Changes in building properties or operation would cause a change in the energy signature model, affecting one or more of the coefficients discussed above. Therefore, the savings potential of an energy saving measure can be estimated by adjusting model coefficients and parameters to reflect proposed retrofits.

Step 2: Estimating Changes to Energy Signature Models

This section describes the method of estimating changes to the energy signature models to estimate energy use after an energy efficiency retrofit. The method is demonstrated using a 3PH model. Equation 2 shows that there are four coefficients F_i, HS, $T_{b,H}$ and PD and two variables T_{oa} and P, that influence fuel use. F_i, PD and P are weather-independent and therefore will be assumed to remain constant and will not be considered further. Therefore, modifications are made to the coefficients HS and $T_{b,H}$ to estimate savings of proposed retrofits.

The proposed HS is calculated as the energy signature model derived HC adjusted for the estimated change in HC, ΔHC divided by the proposed heating equipment efficiency. The proposed heating equipment efficiency is equal to the baseline efficiency adjusted for proposed equipment efficiency improvements. The calculation of the proposed HS is shown in Equation 9. ΔHC is the sum of the expected change of the building heating load and the expected change of outdoor ventilation and infiltration air. This calculation is shown in Equation 10.

$$HS_{Proposed} = \frac{HC - \Delta HC}{\eta_H - \Delta\eta_H} \quad (9) \qquad \Delta HC = \Delta UA + \Delta V\rho c_p \quad (10)$$

Common examples of retrofits which would result in a ΔUA are adding insulation to the envelope of a building and replacing exterior windows with units that have a higher insulation value. Common examples of retrofits which would result in a $\Delta V\rho c_p$ are closing outdoor air dampers during unoccupied periods and reducing infiltration by improving the sealing of the building envelope. Calculating ΔHC requires measuring or estimating the change in building envelope thermal resistance or the reduction of ventilation or infiltration air.

The balance temperature also must be recalculated when proposed retrofits affect any of the following, T_{set}, Q_i or HC. The proposed balance temperature calculation is shown in Equation 11.

$$T_{b,H,Proposed} = (\mathrm{T_{set}} - \Delta\mathrm{T_{set}}) - \frac{\mathrm{Q_i} - \Delta\mathrm{Q_i}}{\mathrm{HC} - \Delta HC} \quad (11)$$

Changes in T_{set} commonly result from lowering the space temperature set-point during the heating season, including night setback controls. Changes in Qi can result from retrofits which influence internal solar heat gains such as replacing opaque fiberglass windows with clear glass windows.

A visual representation of the effect on energy signature models due to changes to model coefficients and parameters is shown in Figure 2.

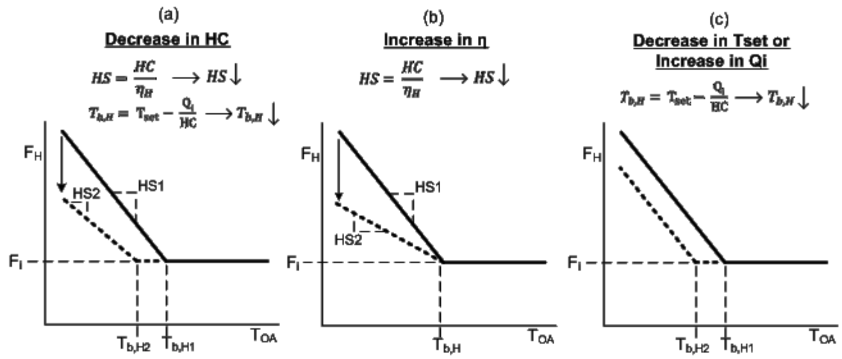


Figure 2 *3PH energy signature model changes due to: (a) decrease in HC, (b) increase in efficiency of heating system, (c) decrease in T_{set}, and decrease in weather-independent energy use.*

Step 3: Normalized Annual Energy Savings

The proposed model can now be formed by substituting the calculated proposed HS and $T_{b,H}$ into Equation 2, the new model is shown in Equation 12.

$$F_{proposed} = F_i + HS_{proposed} \cdot (T_{b,H,proposed} - T_{OA})^+ + PD \cdot P \tag{12}$$

The energy savings due to retrofits is calculated as the sum of the differences between the baseline model and proposed model driven with typical weather data.

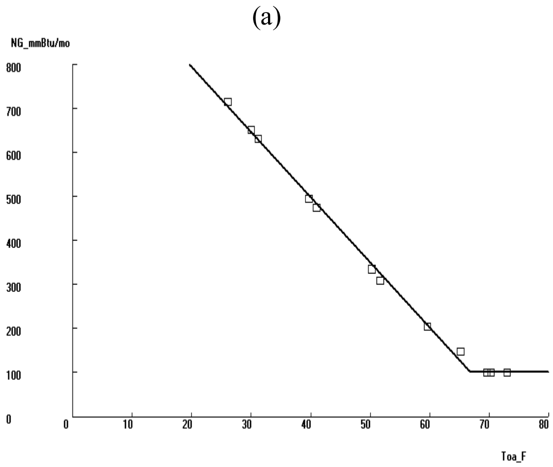
$$F_{Savings} = \sum\left[\left(HS_{Base} \cdot (T_{b,H,Base} - T_{OA})^+\right) - \left(HS_{proposed} \cdot (T_{b,H,proposed} - T_{OA})^+\right)\right] \tag{13}$$

The typical weather data used in this analysis is TMY2 weather data. This data is input into the simulation model and run through Equation 13 on an hourly basis and summed to find the normalized annual savings (NAS). The NAS can also be calculated using TMY2 weather data reformatted into Bin temperature data or HDH and CDH.

COMPARISON OF INVERSE AND FORWARD SIMULATED SAVINGS

An important question is how well can a simple three-parameter model of monthly billing data versus outdoor air temperature characterize actual building energy use; and further, how closely do savings estimated using the inverse simulation method described here compare to savings estimated using traditional forward energy simulation. To explore these questions, a hypothetical industrial facility was modeled using the hour-by-hour simulation program (Kissock, 1997). Simulated hourly fuel use was then aggregated to the monthly timescale, and a three-parameter model of fuel use versus outdoor air temperature was developed. The model is shown in Figure 3a, and steady-state coefficients from the simulation and statistical coefficients from the regression model are shown in Table 1. Comparison of the simulated and statistically-derived building parameters reveals strong agreement, except for internal heat gain, Q_i Moreover, the overall fit of the model is excellent with an $R^2 = 1.00$, indicating that a 3PH model can effectively characterize heating fuel use in simple industrial buildings.

When May and September are removed from the statistical model, the agreement between simulated and statistically-derived building parameters becomes even stronger (Table 1 and Figure 3b). The improved agreement occurs because the statistical model correlates fuel use with average outdoor air temperature, rather than heating degree hours. During winter, average outdoor air temperatures are well below balance temperature $T_{b,H}$, and the error is negligible. However during swing months, the difference between average outdoor air temperature and heating degree hours increases. This error during swing months increases the uncertainty with which the balance temperature and independent energy use can be determined by the inverse model.



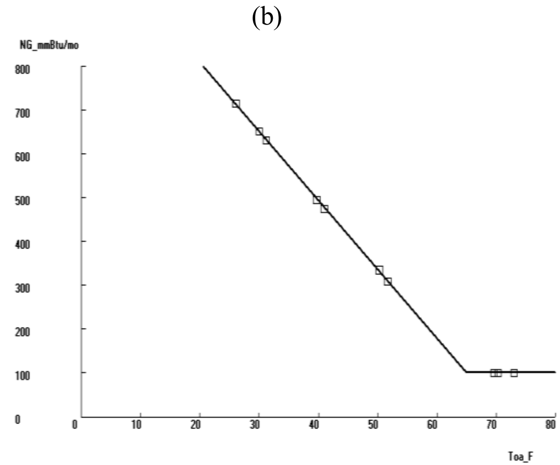


Figure 3 3PH energy signature models: (a) May and September included, (b) May and September removed.

Table 1. Baseline 3PH Coefficients

	Baseline Theoretical	Baseline Statistical w/ May, Sep.	Baseline Statistical w/o May, Sep.	Proposed Statistical
Fi, mmBtu/mo (GJ/mo)	100.00 (105.51)	100.07 (105.58)	100.09 (105.60)	100.09 (105.60)
HS, mmBtu/mo-F (GJ/mo-K)	15.70 (9.20)	14.81 (8.68)	15.76 (9.24)	13.82 (8.10)
HC, Btu/hr-F (W/K)	17,200 (2.80)	16,228 (2.64)	17,274 (2.81)	15,140 (2.47)
$T_{b,H}$, F (C)	64.05 (17.81)	66.87 (19.37)	64.96 (18.31)	64.25 (17.92)
Q_i, Btu/hr (kW)	102,360 (30.00)	50,793 (14.89)	87,060 (25.51)	87,060 (25.51)

Predicting Savings Using Inverse Simulation

To compare savings estimated by the statistical inverse simulation method with simulated savings, proposed model coefficients were calculated to be F_i = 100.09, HS = 13.82 and $T_{b,H}$= 64.25 (F) using Equations 9, 10, and 11. Next, TMY2 weather data were used to calculate fuel use for both the baseline and proposed cases on an hourly basis. The hourly fuel use was summed to calculate the NAC for both the baseline and proposed cases. Table 2 shows that the inverse statistical method predicted normalized annual consumption, NAC, to within $\pm$ 1.2% of simulated NAC in both the baseline and proposed cases. Further, normalized annual savings, NAS, were also predicted within $\pm$ 1% of simulated savings. These results demonstrate the ability of the inverse simulation method to predict savings within an acceptable margin of error.

Table 2. Baseline and Proposed Normalized Annual Consumptions and Savings

	Baseline			Proposed		
	Simulated	Statistical	% diff.	Simulated	Statistical	% diff
NAC, mmBtu/yr (GJ/yr)	3,050 (3,218)	3,083 (3,253)	1.1	2,595 (2,738)	2,625 (2,770)	1.2
NAS mmBtu/yr (GJ/yr)	-	-		455 (480)	459 (484)	0.9

INDUSTRIAL FACILITY CASE STUDY

This case study demonstrates the method by applying it to an industrial facility located near Dayton, Ohio. An employee awareness program was instituted in late 2006 to reduce space heating costs. The program encouraged employees to shut off exhaust fans when not needed, lowering the amount of infiltration air during the winter. Energy savings Fuel consumption data before and after the implementation of the program is analyzed below to determine the energy savings.

Figure 4a shows the baseline (squares) and post (circles) fuel energy use for the facility, with baseline (blue) and post (red) energy signature models. The models show that at any given temperature, natural gas use decreased during the post period. Figure 4b shows the same baseline model (blue), however, the proposed model was created by reducing the heating slope, HS, to conform to the aforementioned changes in plant ventilation practices. Note that reducing the heating slope, HS, also reduced the balance temperature, $T_{b,H}$, as expected. Comparison of the two plots, shows that the measured post model in Figures 4a is very similar to the proposed model in Figure 4b, indicating that the change in energy use patterns is accurately modeled using this method as a simple change in heating slope.

(a) (b)

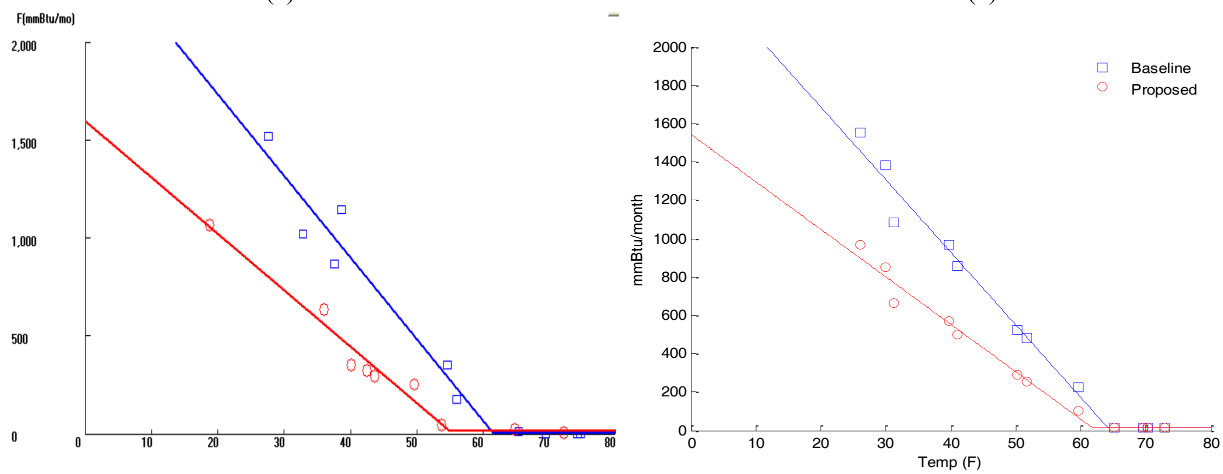


Figure 4 (a) measured fuel use data with 3PH models (b) ISim predicted data and 3PH models.

Model coefficients are listed in Table 3. The measured coefficients are derived from statistical 3PH models of the measured data. The ISim baseline coefficients are identical to the measured baseline coefficients. The ISim proposed coefficients by decreasing infiltration by 13,000 cfm (6,135 L/s), which decreased heating slope and balance temperature. Normalized annual consumption and savings are also listed in Table 3. Normalized annual consumption (NAC) is calculated by driving the models with TMY2 data to estimated energy use during a typical weather year. Normalized annual savings (NAS) are the difference between the baseline and post (or proposed) NACs.

The results show that reducing the HC as described above, resulted in an ISIM proposed model which was very similar to the measured post-retrofit model. Further, ISim predicted NAS within 14% of measured NAS. Since the heating slopes (HS) are nearly identical, the error between predicted and measured NAS can be attributed to small differences in Fi and Tb,H. Some of this difference is probably attributable to changes in plant operation. However, as discussed in the simulation section, some may be attributable to modeling error. Thus, the 14% difference represents the upper bound on modeling error in this case study.

Table 3. Case Study 3PH Coefficients

	Pre	Post	ISim Baseline	ISim Proposed
Fi, mmBtu/mo (GJ/mo)	2.50 (2.64)	13.56 (14.31)	2.50 (2.64)	2.50 (2.64)
HS mmBtu/mo-F (GJ/mo-K)	41.69 (24.44)	28.83 (16.90)	41.69 (24.44)	28.88 (16.93)
$T_{b,H}$, F (C)	61.54 (16.41)	54.93 (12.74)	61.54 (16.41)	57.79 (14.33)
NAC, mmBtu/yr (GJ/yr)	6,819 (7,194)	3,467 (3,658)	7,010 (7,396)	4,128 (4,355)
NAS, mmBtu/yr (GJ/yr)		3,351 (3,535)		2,882 (3,041)

SUMMARY AND CONCLUSION

This paper describes an inverse simulation method of estimating energy savings in industrial and simple buildings. The method begins by developing a multivariate three-parameter change-point regression model of facility energy use. Next, the change in model parameters is estimated to reflect the proposed energy saving measure. Energy savings are then estimated as the difference between the base and proposed models driven with typical weather data. Expected savings from inverse simulation were compared to savings predicted by detailed hourly simulation, and sources of error were discussed. The method was applied to a case study example.

Use of this method eliminates the need for estimating building parameters, system performance, and operating practices since they are included in the inverse simulation model. It also eliminates the need for model calibration since the inverse model is derived from actual energy use data. Thus, this method may be less time intensive and more accurate than traditional methods of estimating savings.

Future work seeks to better understand and decrease the error in energy signature models, especially the error due to averaging energy, production and weather data over long time scales. For example, average temperatures do not fully capture "degree-hour" effects, and average energy use and production does not fully capture changes in facility operation and internal loads. In addition, future work should test the method on more facilities to identify weaknesses and opportunities for improvement.

REFERENCES

Eger, B. and Kissock, K., 2007, "Understanding Industrial Energy Use through Sliding Regression Analysis", ACEEE Summer Study on Energy in Industry, White Plains, NY, July 24-27.

Fels, M. 1986a. Special Issue Devoted to Measuring Energy Savings: The Scorekeeping Approach, *Energy and Buildings* Vol. 9, Nums 1 & 2, February.

Goldberg, M. and Fels, M. 1986. Refraction of PRISM Results in Components of Saved Energy, *Energy and Buildings*, Vol. 9, Nums 1 & 2, February.

Haberl. J., Sreshthaputra, A., Claridge, D.E. and Kissock, J.K., 2003. "Inverse Modeling Toolkit (1050RP): Application and Testing", ASHRAE Transactions, Vol. 109, Part 2, pp. 435-448.

Kissock, K. 1997. "ESim Building Energy Simulation Software", University of Dayton, Dayton, OH.

Kissock, K., Reddy, A. and Claridge, D. 1998. Ambient-Temperature Regression Analysis for Estimating Retrofit Savings in Commercial Buildings, *ASME Journal of Solar Energy Engineering*, Vol. 120, No. 3, pp. 168-176.

Kissock, J.K. 1999. UD EPA Average Daily Temperature Archive, academic.udayton.edu/weather/.

Kissock, J.K., Haberl J. and Claridge, D.E. 2003. Inverse Modeling Toolkit (1050RP): Numerical Algorithms, *ASHRAE Transactions*, Vol. 109, Part 2.

Kissock, K. 2005. "Energy Explorer", Energy Information Systems, Dayton, OH.

NREL 1995. National Renewable Energy Laboratory, 1995, User's Manual for TMY2s

Rabl, A. 1988. Parameter Estimation in Buildings: Methods for Dynamic Analysis of Measured Energy Use, *ASME Journal of Solar Energy Engineering*, Vol. 110, pp. 52 - 62.

Rabl, A., Norford, L. and Spadaro, J. 1992. Steady State Models for Analysis of Commercial Building Energy Data, *Proceedings of the ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, CA,* August, 9.239-9.261.

Reddy, A. 1989. Identification of Building Parameters Using Dynamic Inverse Models: Analysis of Three Occupied Residences Monitored Non-Intrusively. Center for Energy and Environmental Studies, Princeton University.

Reddy, T., J. Kissock, and D. Ruch. 1998. Uncertainty in baseline regression modeling and in determination of retrofit savings. ASME Journal of Solar Energy Engineering 120(3): 185-192.

Ruch, D., Chen, J. Haberl, and D. Claridge. 1993. A changepoint principal component analysis (CP/PCA) method for predicting energy usage in commercial buildings: The PCA model. ASME Journal of Solar Energy Engineering 115(2): 77-84.

Sever and Kissock 2009. ISim, University of Dayton, Dayton, OH.