Assessment of the U.S. Department of Energy's Home Energy Scoring Tool

David Roberts, Noel Merket, Ben Polly, Mike Heaney, Sean Casey, and Joseph Robertson
National Renewable Energy Laboratory

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July 2012

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[1] In acknowledging individuals and organizations we do not mean to imply their endorsement of the research results. Our intention is simply to acknowledge their contributions and thank them.

Executive Summary

The National Renewable Energy Laboratory (NREL) conducted a series of assessments of the U.S. Department of Energy's (DOE) proposed Home Energy Scoring Tool (HEST). The primary objective of this work was to assess the accuracy of HEST as it was being developed and to provide information useful to DOE program managers and HEST development team at Lawrence Berkeley National Laboratory.

NREL assessed the accuracy of HEST from the version used for the Home Energy Score pilot, released January 26, 2011, through the April 27, 2012 release. With the exception of Appendix A, Historical Progression of HEST Accuracy, this report reflects assessment of the April 27, 2012 release of HEST.

Comparison of Predicted Energy Uses to Measured Energy Uses

Predictions of electricity and natural gas (NG) consumption were compared with weather-normalized utility billing data for a mixture of newer and older homes located in Oregon, Wisconsin, Minnesota, North Carolina, and Texas.[2] The 859 electricity comparisons and 500 NG comparisons yielded the following:

- HEST underpredicted electricity use by a median of 1%.
- HEST underpredicted NG use by a median of 10%.

The primary objective of the Home Energy Score program is to issue a score to the homeowner. The Score ranges from 1 to 10, where a home scoring a 1 uses the most energy and a home scoring a 10 uses the least. For 52% of the homes in this sample, the predicted Home Energy Score is within ±1 point of a score calculated from measured energy use.[3]

Comparison of Predicted Energy Uses to Predictions From Other Tools

Similar comparisons were made between predictions from two other commonly used residential energy analysis software tools, REM/Rate and SIMPLE, and weather-normalized utility billing data for the same set of homes. The results of the comparisons are presented along with those from HEST in Table ES–1 and Table ES–2.

HEST energy use predictions compare well with the other two energy analysis software tools.

[2] A limitation of this approach is that the Home Energy Scoring Tool assesses the performance of the energy-related assets of a home under typical operating conditions, while utility billing data reflect the performance of the energy-related assets of a home under actual operating conditions. The uncertainty associated with this limitation is addressed in later sections of the report.
[3] The scores were determined using source energy bin definitions released by DOE on May 19, 2012.

Table ES–1. Statistical Summary of Differences Between Predicted and Measured Electric Energy Use (Predicted kWh—Measured kWh)

	HEST	SIMPLE	REM/Rate
Number of Observations	859	859	859
Mean Measured	10,945	10,945	10,945
Mean Predicted	10,309	8,800	11,361
Mean Difference	–636	–2,144	416
Median Difference	–115	–1,514	835
Median Absolute Difference	2,424	2,393	2,386
Median Absolute Percent Difference	24%	25%	23%
Percent of Homes < ± 25% Different	54%	49%	52%
Percent of Homes < ± 50% Different	81%	86%	79%

Table ES–2. Statistical Summary of Differences Between Predicted and Measured NG Use (Predicted Therms—Measured Therms)

	HEST	SIMPLE	REM/Rate
Number of Observations	500	500	500
Mean Measured	871	871	871
Mean Predicted	787	688	1,186
Mean Difference	–84	–183	315
Median Difference	–76	–177	256
Median Absolute Difference	193	205	293
Median Absolute Percent Difference	24%	27%	37%
Percent of Homes < ± 25% Different	51%	45%	38%
Percent of Homes < ± 50% Different	83%	89%	60%

Statistical Modeling

To help identify potential issues driving differences between HEST-predicted energy uses and measured energy uses, multiple linear regression analysis was employed to develop empirical models using energy use differences as the dependent variable. The floor area and number of bedrooms were significant contributors to the difference between predicted and actual electric energy consumption of the homes. This may be due in part to assumptions about occupancy, base loads, and lighting in HEST. Contributors to the difference between predicted and measured NG use include the number of heating degree days, window area, and heating system efficiency. The statistical model indicates that HEST is over- or under-responsive to these features to some degree. It is important to note that the statistical model applies only to the current dataset.

Operational Uncertainty Analysis

HEST assesses the performance of the energy-related assets of a home under typical operating conditions (standard occupants). However, utility billing data reflect the performance of the energy-related assets of a home under actual operating conditions, which can vary greatly.

Therefore, when assuming standard occupancy, there is considerable uncertainty that predictions will agree with utility billing data because actual occupant behavior is not considered. The goal of this portion of the analysis was to estimate the effect of operational input uncertainty on the uncertainty in energy use predictions.

Key conclusions from the analysis are:

- Even if all other inaccuracies could be eliminated in an asset analysis, differences between software predictions and measured source energy would be significant because occupant behavior is variable relative to standard assumptions. For example, simulations showed total source energy use differences of up to 36%;[4] the largest percent differences occurred in climates with low space conditioning loads (climates where occupant-driven plug loads dominate).

- Although occupant behavior variability is a significant source of inaccuracy, it does not explain all of the differences observed in the NREL Field Data Repository comparisons. The remaining sources of uncertainty could be targeted to improve HEST. For example, assessment procedures may be adjusted considering tradeoffs in accuracy, cost, and time necessary to perform the assessment.

Whole-House Leakage Sensitivity Analysis

HEST accepts either a quantitative measurement of whole-house leakage using a blower door or a qualitative assessment of whether the home has been air sealed. During the Home Energy Score pilot, blower door measurements were performed for 655 homes. NREL reran these homes through HEST three times using three inputs for whole-house air leakage:

- Blower door data (quantitative input)
- The qualitative assessment of “sealed”
- The qualitative assessment of “unsealed”

On average, when compared to the predictions stemming from quantitative input, the source energy use is increased by 6 MMBtu/yr (2.6%) when the sealed qualitative input was used and by 24 MMBtu/yr (10.6%) when the unsealed qualitative input was used. This could indicate that the leakage area assumptions behind the qualitative inputs are generally overestimating the actual leakages. However, these differences result in an average reduction in the Home Energy Score of only 0.67 points when specifying unsealed qualitative input versus entering measured leakage.

[4] Differences generally followed normal distributions. The 36% value corresponds to two standard deviations in the Los Angeles climate and roughly bounds 95% of the differences.

Nomenclature

ACH50	Air changes per hour at 50 Pascals of pressure differential
CDD	Cooling degree day
CFM25	Cubic feet per minute at 25 Pascals of pressure differential
CFM50	Cubic feet per minute at 50 Pascals of pressure differential
CL	Confidence level
COP	Coefficient of performance
COV	Coefficient of variation
DOE	U.S. Department of Energy
FDR	NREL Field Data Repository
HDD	Heating degree day
HERS	Home Energy Rating System
HES	Home Energy Saver
HESpro	Home Energy Saver Professional
HEST	Home Energy Scoring Tool
HSP	Building America House Simulation Protocols
HSPF	Heating Seasonal Performance Factor
LBNL	Lawrence Berkeley National Laboratory
MEL	Miscellaneous electric load
MGL	Miscellaneous gas load
MLR	Multiple linear regression
NG	Natural gas
NREL	National Renewable Energy Laboratory
o.c.	On center
SD	Standard deviation
SEER	Seasonal Energy Efficiency Ratio
TMY	Typical Meteorological Year

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Figures

Unless otherwise indicated, all figures were created at NREL.

Tables

1 Introduction

The National Renewable Energy Laboratory (NREL) conducted a series of assessments of the U.S. Department of Energy's (DOE) proposed Home Energy Scoring Tool (HEST). The primary objective of this work was to assess the accuracy of HEST as it was being developed and to provide information useful to DOE program managers and HEST development team at Lawrence Berkeley National Laboratory (LBNL).

HEST assessment comprised the following analysis activities:[5]

- Comparison of predicted energy uses to measured energy uses
- Comparison of predicted energy uses to predictions from other tools
- Statistical modeling
- Operational uncertainty analysis
- Whole-house leakage sensitivity analysis.

Preliminary results of these analyses were reported in a series of memos delivered to DOE between May and September 2011. The general content of those memos was updated and organized to produce this report. NREL assessed the accuracy of HEST from the version used for the Home Energy Score pilot, released January 26, 2011, through the version released April 27, 2012. With the exception of Appendix A, Historical Progression of HEST Accuracy, this report is an assessment of the April 27, 2012 release.

1.1 Home Energy Scoring Tool

The Home Energy Score provides homeowners with a simple way to compare the relative energy use of their homes. Utilizing information collected by a professional conducting an assessment of the home's energy-related features, the Home Energy Scoring Tool generates a score from 1 to 10, where a home scoring 1 uses the most energy and a home scoring 10 uses the least.[6] HEST produces a Home Energy Score label (see Figure 1).

[5] This analysis was conducted multiple times during the development of HEST. The LBNL development team used the results to improve the overall accuracy of HEST. The results presented in the body of this report include those improvements; further discussion about earlier analyses and resulting changes to HEST are included in Appendix A.
[6] Thus, the implied precision of the assessment is not intended to be better than 20% (±10%) of actual energy use.

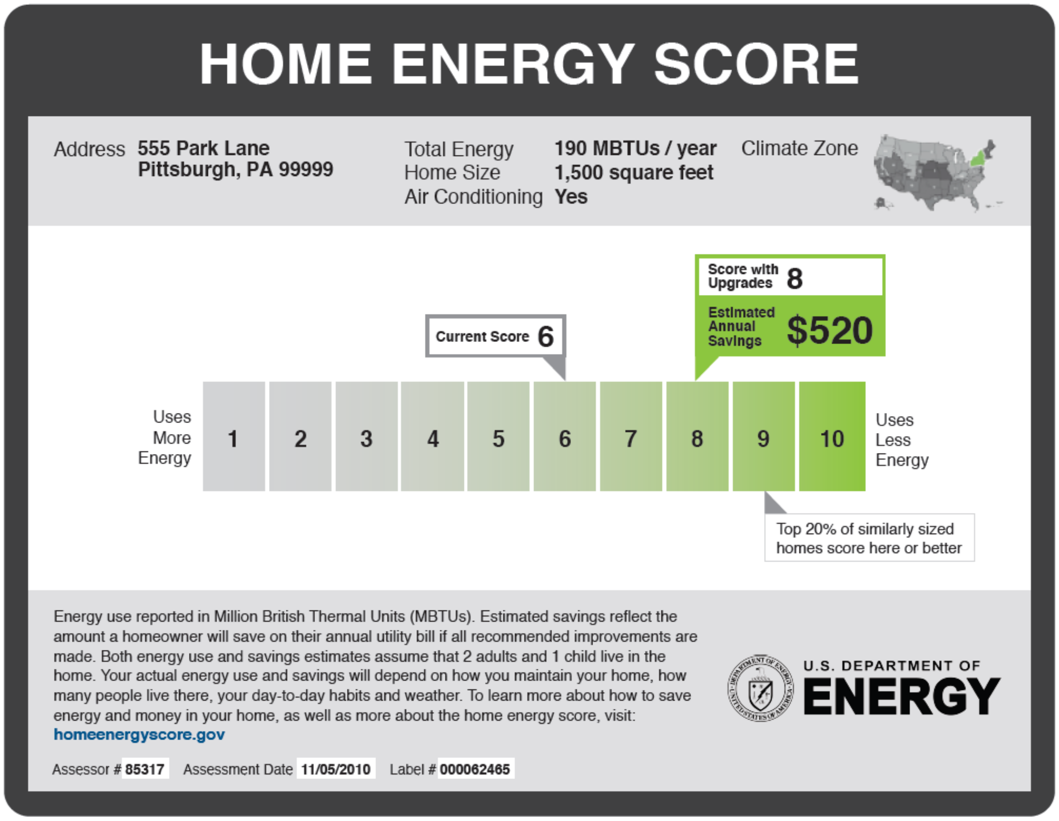

Figure 1. Sample Home Energy Score label

(source: DOE Office of Energy Efficiency and Renewable Energy website)[7]

The Home Energy Scoring Tool is a variation of LBNL's Home Energy Saver (HES) and Home Energy Saver Pro (HESpro). HES and HESpro are Web-based applications that generate estimates of energy use and potential retrofit savings for homeowners and professionals, respectively. HEST requires fewer inputs than HES or HESpro. HEST intentionally does not take any input about the actual occupants of the home, including the way the occupants operate the home (e.g., thermostat set points) and certain appliances (e.g., second refrigerator, aquariums, waterbeds). Instead, typical occupancy is assumed, resulting in an assessment of the home's energy performance under standard operating conditions that can be fairly compared to assessments of the energy performance of other homes under the same standard conditions.

The score is determined from the predicted source energy use of the home. Scoring bins have been developed for each of 245 climate locations throughout the country. The score for the home depends on the bin in which the predicted source energy use falls.

Detailed documentation of HEST is available online at the following website: https://sites.google.com/a/lbl.gov/hes-public/home-energy-scoring-tool.[8]

[7] Label at time of reporting. Final label may differ.
[8] The content of the documentation on this website is likely to be updated as HEST continues to evolve; it may not reflect the version that was assessed in this report.

1.2 Home Energy Score Pilot

In early 2011 DOE conducted a pilot of the Home Energy Score with 10 agencies, spread throughout the United States, who volunteered to test the concept. The agencies conducted dozens to hundreds of home assessments, entered data collected into the pilot version of the HEST Web interface, and generated Home Energy Score labels. The pilot participants provided feedback to DOE on several aspects of the proposed program (homeowner interest and acceptance of the score, likelihood of stimulating retrofit activities, ease of use, accuracy, etc).

More than 1,000 homes were scored during the pilot (see Figure 2 for geographic locations). The data collected and results generated are stored in a database accessible by the HEST development team at LBNL. These "sessions" data were provided to NREL for use in this assessment. Of particular interest was the subset of the pilot homes for which blower door tests were conducted to assess whole-house leakage. These data were used in conducting the sensitivity analysis discussed in Section 5.

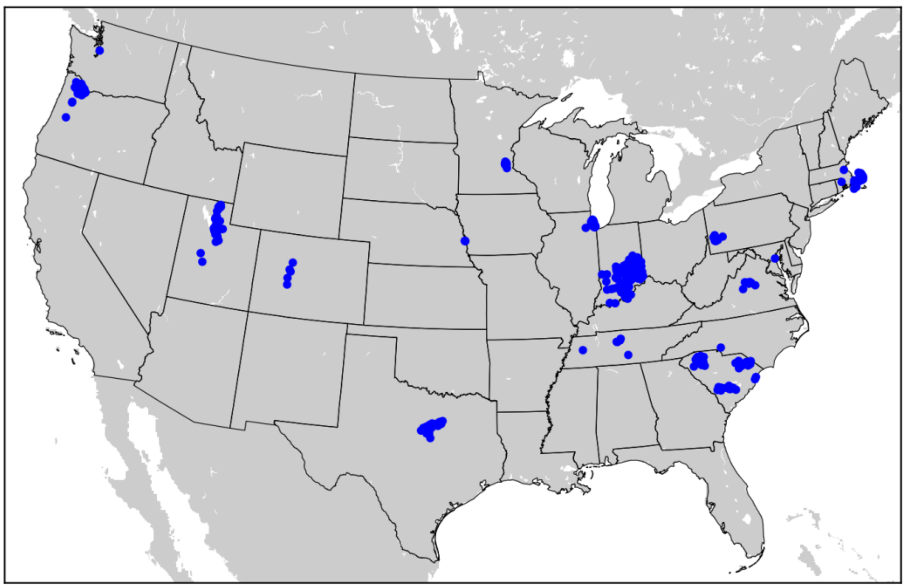

Figure 2. HEST pilot locations

1.3 Field Data Repository

NREL's Field Data Repository (FDR), under development at the time of preparing this report, is a collection of historical datasets that contain energy-related characteristics and utility billing data for homes. Figure 3 shows a schematic overview of the FDR and related tools. The overarching objective of the FDR project is to collect and organize disparate historical and future datasets into a singular repository for use by the research community. The FDR supports NREL's broader efforts to assess and improve the accuracy of residential energy analysis methods, as described in Polly et al. (2011).

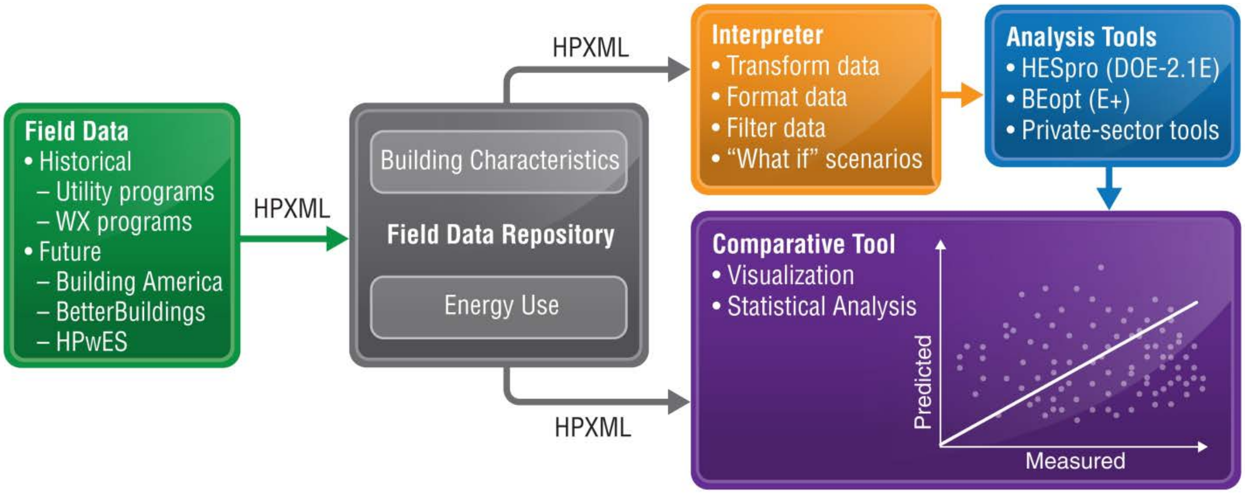

Figure 3. Schematic overview of the FDR

NREL's assessment of HEST largely coincided with the initial development of the FDR. NREL had been collecting historical datasets and was just beginning to organize these into a singular repository, and to build tools to support the application, when the HEST assessment project began. The HEST assessment project was the first application of FDR capabilities. Figure 4 shows the geographic distribution of data in the FDR at the time of its use for this assessment.

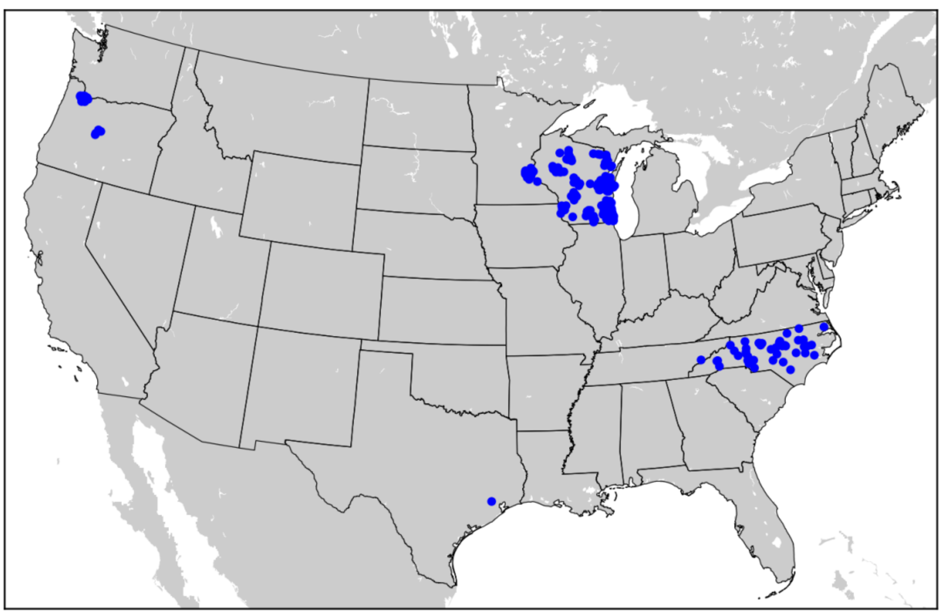

Figure 4. Geographic distribution of data in the FDR as of spring 2012

For this project, NREL developed an "interpreter" to map house characteristics data from the FDR to HEST. The interpreter facilitated comparing predicted energy uses from HEST to weather-normalized measured energy uses stored in the FDR.

Translating data from the FDR to inputs for a particular energy analysis tool is challenging and can introduce some uncertainty into the process. For example, if energy analysis software offers discrete choices of attic insulation R-value, and none of the choices perfectly match the value in the FDR, some uncertainty is introduced when the interpreter makes the most logical, though imperfect, choice in the software.

The FDR, data sources, and data translation are discussed in more detail in Appendix B.

1.4 Overview of Approach

Predicted energy uses from HEST were compared to measured energy uses (i.e., weather-normalized utility billing data). Similarly, predicted energy uses from two other residential energy analysis tools were compared to measured energy uses. The FDR and supporting translation software were used to conduct these comparative analyses. The results of the comparative analyses are presented and discussed in Section 2.

Multivariate linear models of measured energy use and of the residuals between predicted and measured energy uses were developed to examine the impacts of HEST inputs. These models inform potential changes to the software that may improve agreement between predictions and measurements. Results of the statistical modeling are presented in Section 3.

The Home Energy Score assesses the performance of a home's energy-related assets under typical operating conditions (standard occupants). On the other hand, utility billing data reflect the performance of a home's energy-related assets under actual operating conditions, which may not be typical. A Monte Carlo uncertainty analysis was conducted to estimate the portion of the total observed variability between predicted and measured energy uses that is explained by variability in occupant operation of the home. This analysis is described in Section 4.

The HEST input structure allows either a qualitative assessment or a quantitative measurement of whole-house air leakage. A question that is important to DOE is whether to require blower door measurement as part of the Home Energy Score assessment process (currently an optional input). Leveraging data collected during the Home Energy Score pilot, NREL examined the sensitivity to using quantitative versus qualitative input in HEST. This analysis is described in Section 5.

Although the focus of this work is HEST, results of the analyses are reported in terms of energy rather than score because the process of translating energy into a score was in flux at the time this report was prepared. Results and discussion of the score as proposed on May 19, 2012 are included in Section 6.

1.5 Limitations of Approach

There are a number of limitations to using historical datasets to assess software accuracy:

- The datasets may not be representative of the broader population of homes and assessors (who collect the data). Because the data were not collected as part of designed experiments, no statistical sampling procedures were applied. The "catch-as-catch-can" approach will generally result in data that are not statistically scalable to the broader population.

- Historical data were collected for a particular purpose using a specific data collection instrument (e.g., specific rating software). Assessors tend to view a house through the data collection instrument they have been trained to use. Applying data collected for one purpose, at a particular point in time, to other applications is challenging. Significant uncertainty is likely to be introduced when the data are transformed to meet other needs.
- The data collected are generally limited to asset features of the home. Very few operational data are collected. Very little information is collected about atypical energy-using devices (e.g., swimming pools). Measured energy use data (i.e., utility bills) reflect operational variations and atypical energy uses.

1.6 Advantages of Approach

Advantages of an automated, empirical data-driven, population-based approach to assessing software accuracy include:

- Comparing predictions of energy uses to measured energy uses helps address skeptics' concerns that predictions are not accurate. The approach can demonstrate whether software predictions are "right, on average" and provide useful information about level of uncertainty in energy use predictions. Empirically-based testing augments highly detailed software-to-software testing (e.g., BESTEST-EX as described by Judkoff et al. [2010]).
- Using a population of homes in an assessment quantifies uncertainty in predictions across the population and allows stakeholders to assess risks associated with using those predictions.
- Statistical analyses of population data help identify patterns that can be useful in isolating issues that drive errors in predictions. For example, if statistical evaluation of differences between predicted and measured energy use demonstrates that heavily ground-coupled models tend to produce larger average errors, it could indicate a potential issue with ground modeling in the software.
- Automated, data-driven modeling facilitates "what if" analysis. For example, what is the impact of changing standard operational assumptions used in asset assessments? Do answers get "more right, on average?" Such questions can be easily answered programmatically once the framework for running population data through software has been developed.

2 Comparison of Predicted Energy Use to Measured Data

Data from the FDR were programmatically mapped to three energy analysis tools: HEST, SIMPLE, and REM/Rate. Predicted energy uses from these tools are compared to measured energy uses in the following sections: results from HEST are presented and discussed in Section 2.1, results of the SIMPLE analysis are presented in Section 2.2, results for REM/Rate are presented in Section 2.3, and results for all three tools are summarized in Section 2.4.

Of the 1183 homes in the FDR, some were programmatically excluded for a variety of reasons: missing utility billing data, poor data quality, or presence of (known) asset features that cannot be modeled in the analysis tool.[9] The intersection of all the homes successfully simulated in all three analysis tools (859 electric and 500 natural gas [NG]) and the utility bills are compared in the following analysis.

2.1 Scoring Tool

Data from the FDR were mapped to the April 27, 2012 release of LBNL's HEST, submitted to the application programming interface, and the results returned by the application programming interface were collected into a database. The process of mapping FDR data to HEST inputs is detailed in Appendix C.

Figure 5 shows HEST-predicted site electric energy use versus weather-normalized measured site electric energy use. In general, HEST tends to underpredict homes with high measured electric energy use and overpredict electric energy use in homes with low measured use. As discussed earlier, HEST models typical occupancy; thus, it would not be expected to respond to unusually low or high energy use. Even if HEST were perfectly accurate, and all the asset-related inputs were perfectly collected and entered into the software, one would not expect the linear regression line to match the line of perfect agreement because actual occupant behavior is not considered when predicting electric energy use for an asset rating. This is true for all the graphical presentations of predicted versus measured energy use (like Figure 5) in this report. The points to the far right of the graph, well below the line of perfect agreement, are likely homes with electrical loads are that are not considered in the asset assessment: swimming pools, hot tubs, aquariums, waterbeds, second refrigerators, etc. Information about these end uses is not available in the FDR.

[9] The decision about whether a tool can model a particular house configuration or technology is somewhat subjective. The process of translating the FDR data to software inputs is detailed in Appendix C and Appendix D.

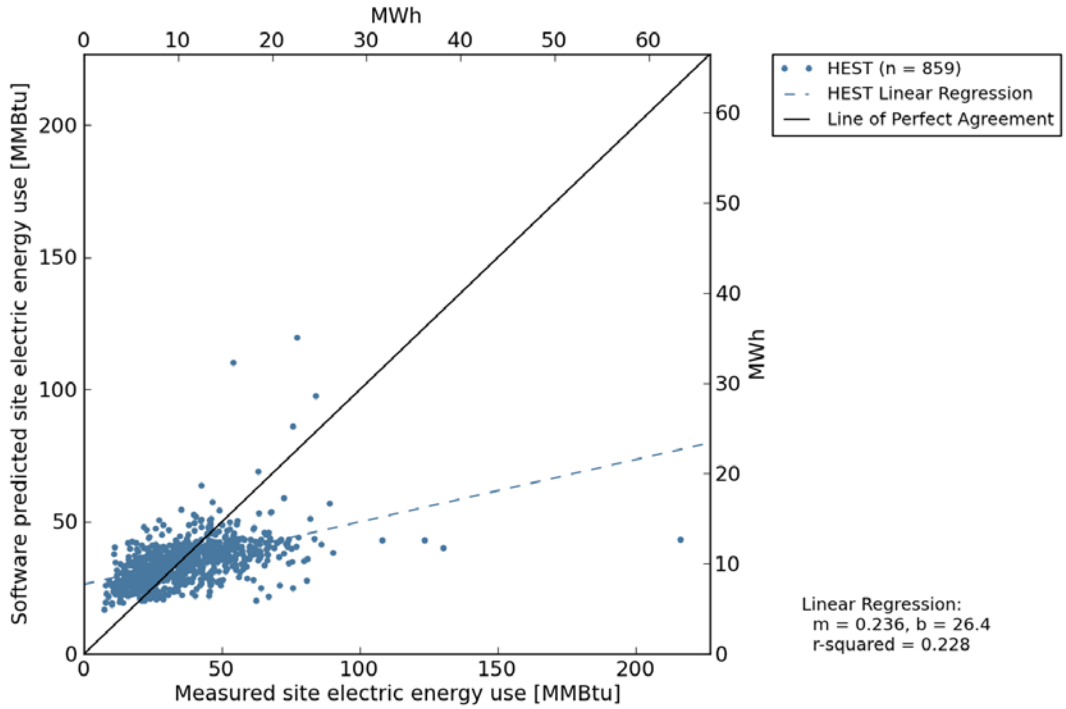

Figure 5. HEST-predicted site electric energy use versus weather-normalized measured site electric energy use

Figure 6 shows the distribution of differences between the HEST-predicted site electric energy use and the weather-normalized measured site electric energy use. The distribution is asymmetrical, with a slight negative bias. Again, this is expected because HEST does not account for extraordinary electric end uses (e.g., swimming pool pumps) and the fact that energy use distributions are not normal: they are bounded by zero, but there is not a bound at the upper limit.

Figure 7 shows HEST-predicted site NG energy use versus weather-normalized measured site NG energy use. The graph indicates generally better agreement than for electric use. Figure 8 shows the distribution of differences between the HEST-predicted site NG energy use and the weather-normalized measured site NG energy use. The distribution is nearly symmetrical around zero, with only a slight negative bias.

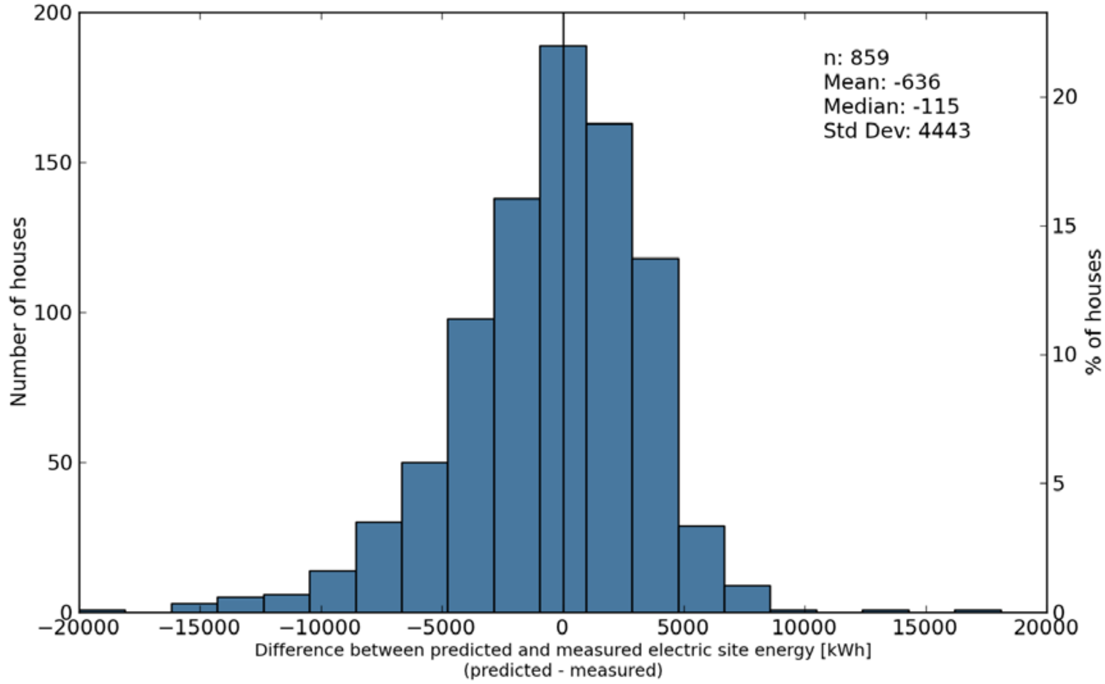

Figure 6. Distribution of differences between HEST-predicted and measured site electric energy use

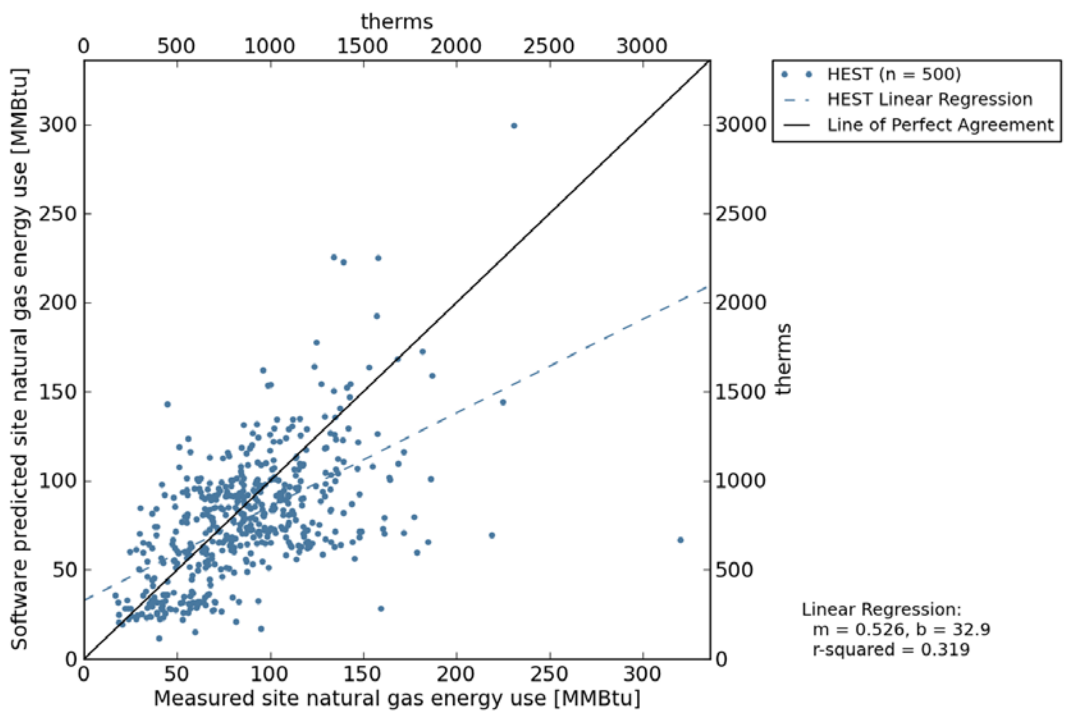

Figure 7. HEST-predicted site NG energy use versus weather-normalized measured site NG energy use

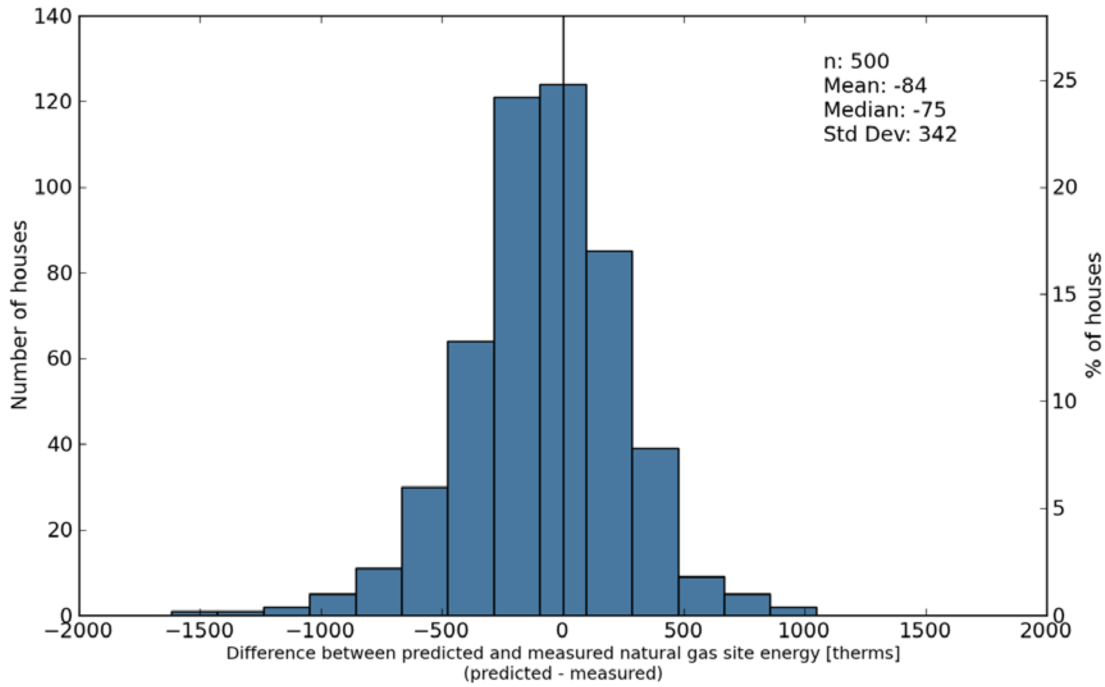

Figure 8. Distribution of differences between HEST-predicted and measured site NG energy use

2.2 SIMPLE Software

The SIMPLE residential energy analysis tool is developed by Blasnik & Associates. SIMPLE is available as a Microsoft Excel spreadsheet and is licensed as the underlying engine for several Web-based energy analysis tools, including Earth Advantage Institute's Energy Performance Score (Earth Advantage Institute, Conservation Services Group 2009). The tool employs a proprietary calculation method. This analysis was conducted with v0.9.11 of the spreadsheet.

Translation of FDR data to SIMPLE inputs is described in detail in Appendix D. Translation of data collected using one analysis tool instead of another is not an exact science. Each tool has a unique "view" of a home, which influences the way an assessor looks at the home. For example, SIMPLE largely employs qualitative inputs rather than quantitative inputs; data collected via REM/Rate, and populating the FDR, are largely quantitative. Blasnik & Associates provided some guidance about the development of the FDR-to-SIMPLE translation software, but the authors recognize that the inexact nature of the process impacts the results.

Figure 9 shows SIMPLE-predicted site electric energy use versus weather-normalized measured site electric energy use. Figure 10 shows the distributions of differences between the SIMPLE-predicted site electric energy use and the weather-normalized measured site electric energy use. The overall predictive trend of SIMPLE is very similar to HEST; the slope of the regression line and standard deviation (SD) of the distribution are nearly identical. SIMPLE does, however, underpredict electricity use to a greater degree than HEST, with a median difference of –1,514 versus –115 kWh.

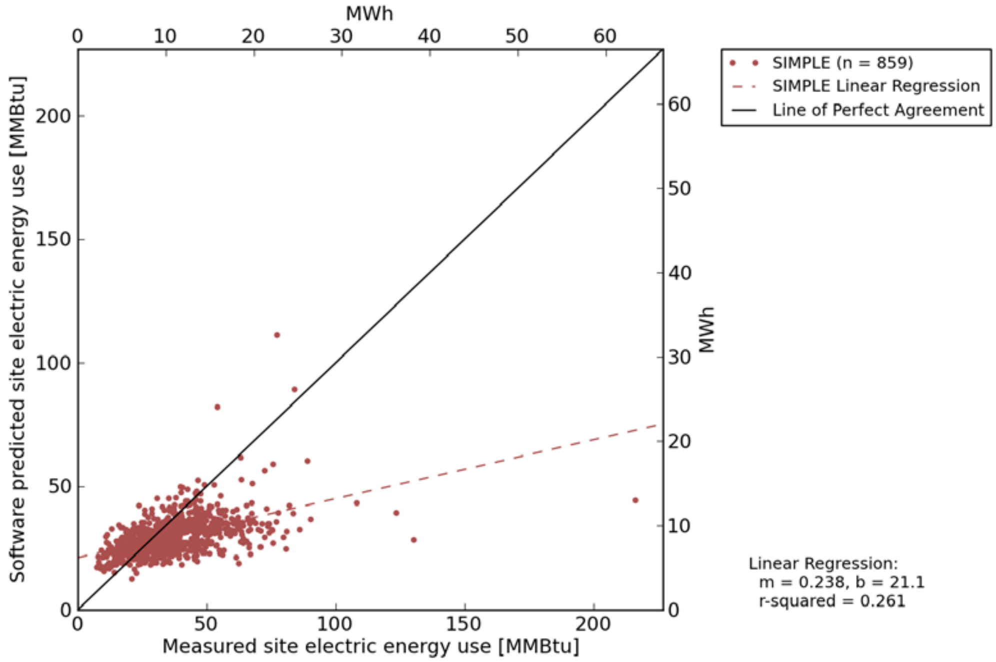

Figure 9. SIMPLE-predicted site electric energy use versus weather-normalized measured site electric energy use

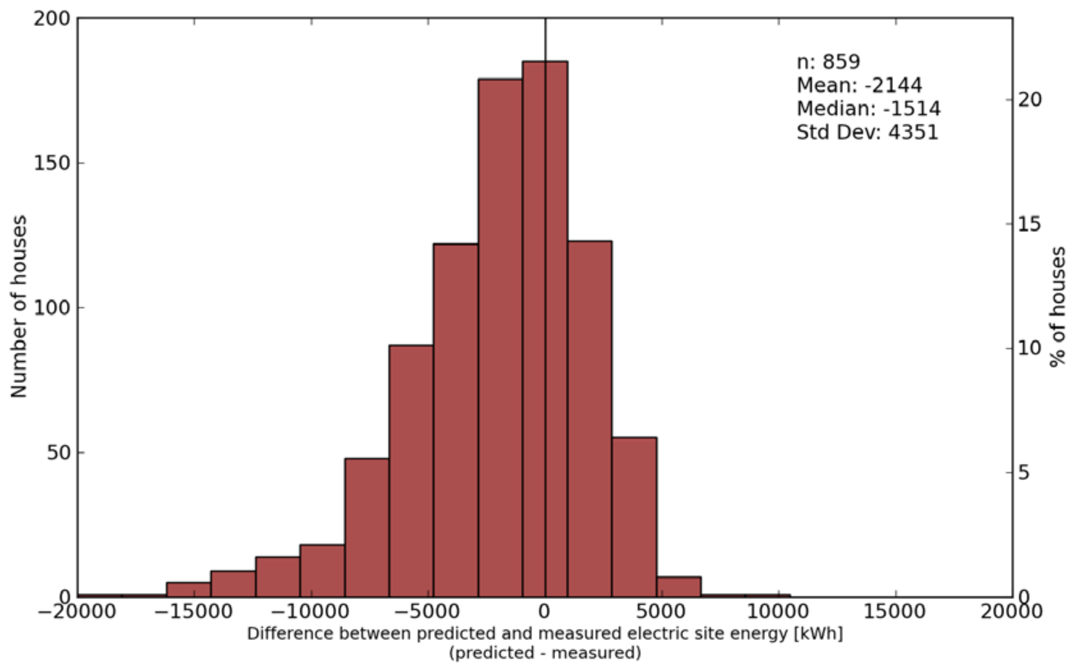

Figure 10. Distribution of differences between SIMPLE-predicted and measured site electric energy use

Figure 11 shows SIMPLE-predicted site NG energy use versus weather-normalized measured site NG energy use. As seen with HEST, SIMPLE was better able to accurately predict NG use than site electricity consumption. Figure 12 shows the distribution of differences between the SIMPLE-predicted site NG energy use versus the weather-normalized measured site NG energy use. SIMPLE predictions of gas use trend with measured values a little better than HEST, with a regression slope closer to unity, and a smaller standard deviation in the distribution of differences. But like the electricity use predictions, SIMPLE tends to underpredict NG use to a greater degree than HEST, with a median difference of –177 versus –76 therms.

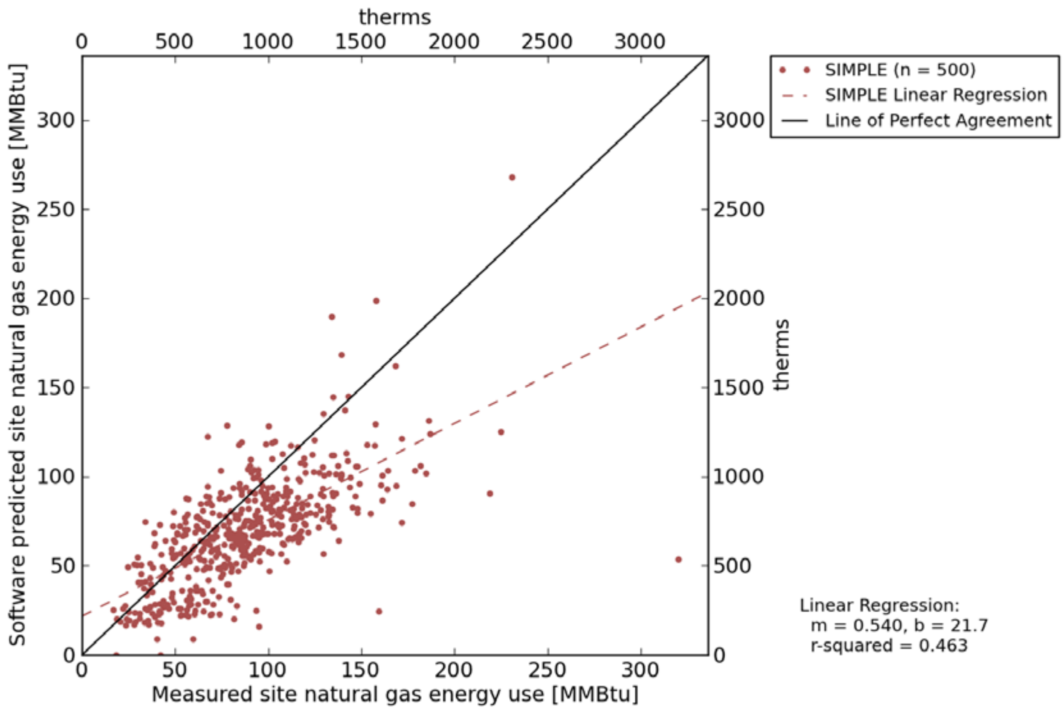

Figure 11. SIMPLE-predicted site NG energy use versus weather-normalized measured site NG energy use.

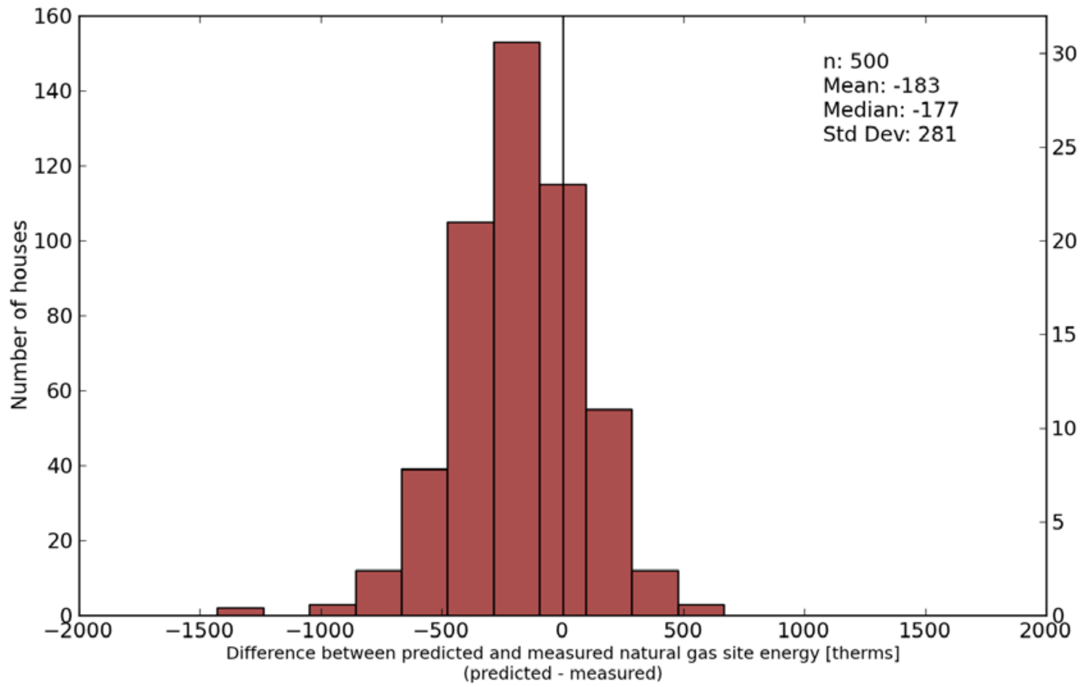

Figure 12. Distribution of differences between SIMPLE-predicted and measured site NG energy use.

2.3 REM/Rate Software

The REM/Rate home energy rating software is developed by Architectural Energy Corporation. It is widely used in home energy rating systems (HERS) to predict energy use and energy savings in new and existing homes. The software employs a proprietary calculation method and is distributed as a Microsoft Windows application. This analysis was conducted with v12.93 of REM/Rate software, except for the Houston homes, which were simulated in v12.41 (74 homes) and v12.51 (8 homes).[10]

Because the FDR is currently based on the REM/Rate Export Database, there is no need to translate the FDR data to REM/Rate inputs. Predicted energy use is generated by REM/Rate and exported to the database along with the house characteristics data.

Figure 13 shows REM/Rate-predicted site electric energy use versus weather-normalized measured site electric energy use. Figure 14 shows the distributions of differences between the REM/Rate-predicted site electric energy use and the weather-normalized measured site electric energy use. REM/Rate electric use predictions trend much better than HEST, with a regression slope much closer to unity. However the standard deviation of the distribution of differences is actually larger than for HEST, indicating more scatter in differences between predicted and measured energy use. Also REM/Rate tends to overpredict electric energy use on average, whereas HEST tends to underpredict.

[10] The data from Houston were originally collected and simulated in older versions of REM/Rate.

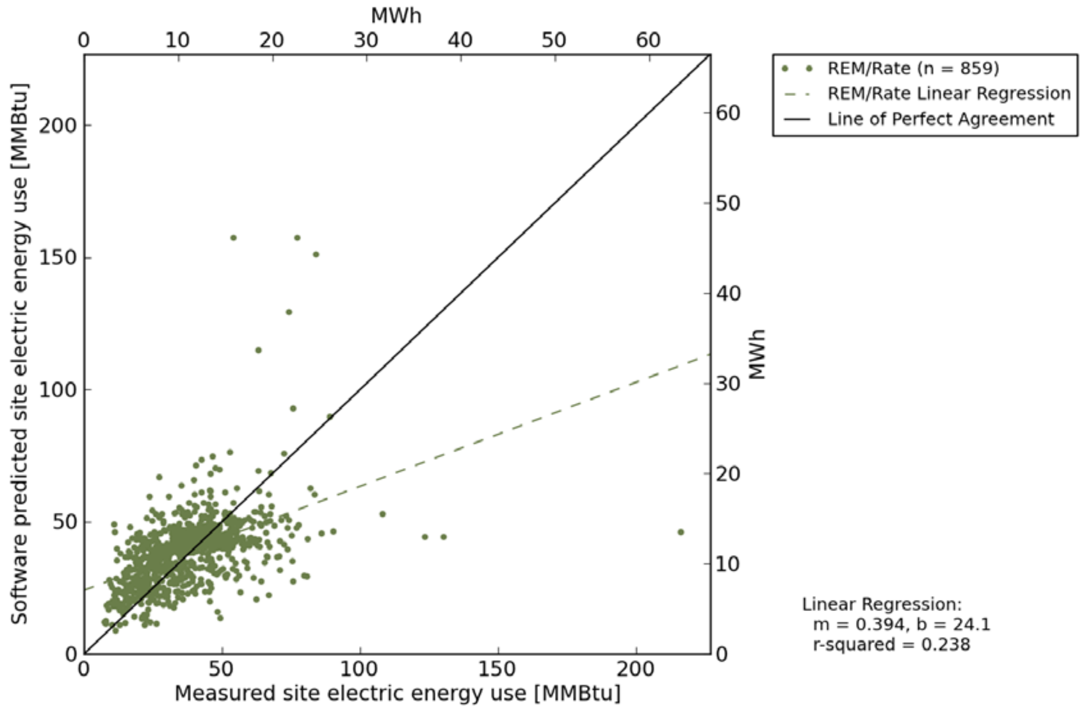

Figure 13. REM/Rate-predicted site electric energy use versus weather-normalized measured site electric energy use

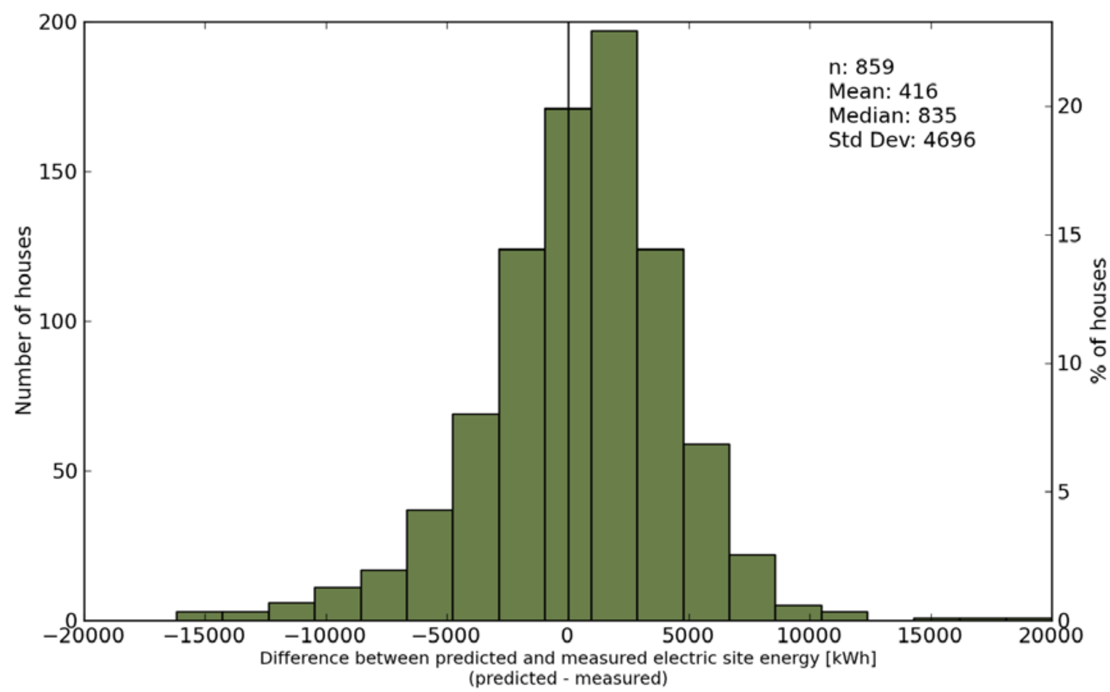

Figure 14. Distribution of differences between REM/Rate-predicted and measured site electric energy use

Figure 15 shows REM/Rate-predicted site NG energy use versus weather-normalized measured site NG energy use. Figure 16 shows the distribution of differences between the REM/Rate-predicted site NG energy use versus the weather-normalized measured site NG energy use. Examination of the distribution reveals a systematic overprediction bias for NG consumption within REM/Rate.

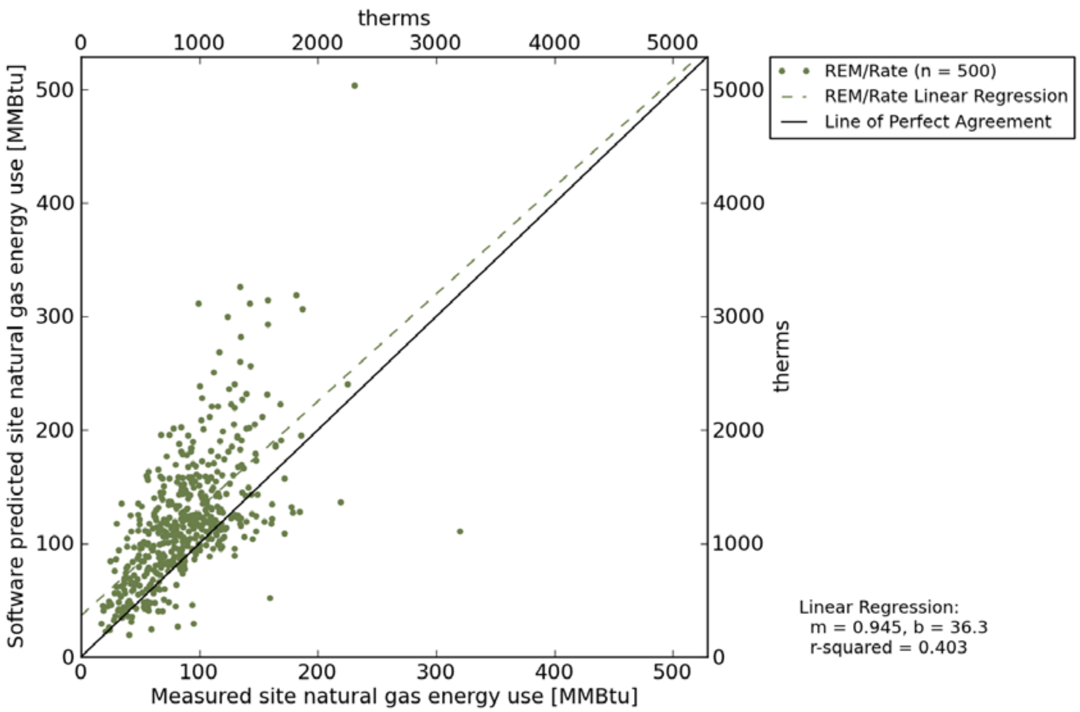

Figure 15. REM/Rate-predicted site NG energy use versus weather-normalized measured site NG energy use

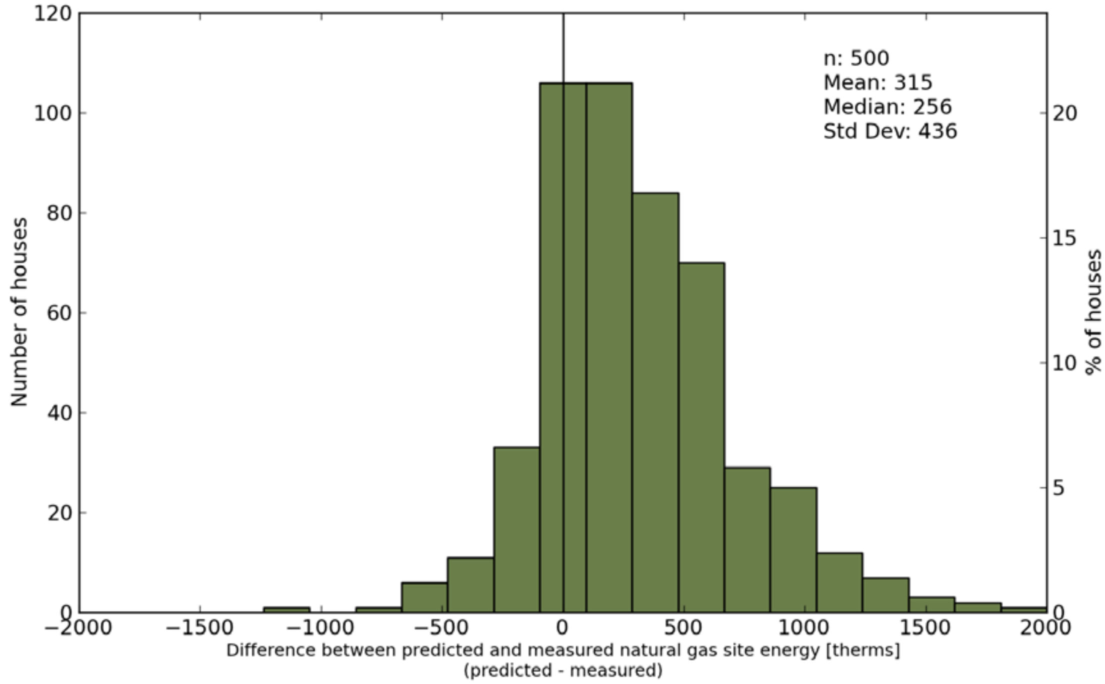

Figure 16. Distribution of differences between REM/Rate-predicted and measured site NG energy use

2.4 Summary

Table 1 summarizes the differences between predicted and weather-normalized measured electric energy uses for the three analysis tools. Table 2 summarizes the differences between predicted and weather-normalized measured NG use.

Of the tools evaluated, HEST has the smallest median difference between predicted and measured electric energy use: –115 kWh/yr versus –1,514 for SIMPLE and 835 for REM/Rate, though the overall difference in this value between the three tools is small, less than 9%. HEST had the highest percentage of homes with predicted electric energy use within ±25% of the measured electric energy use; 54% of the homes were within this range

The median difference between the NG use predicted by HEST and the measured gas use is –76 therms. This can be compared to –177 therms for SIMPLE and 256 therms for REM/Rate. Of the three tools, HEST had the highest percentage of homes with predicted gas use within ±25% of the measured gas use; 51% of the homes were within this range.

Table 1. Statistical Summary of Differences Between Predicted and Weather-Normalized Measured Electric Energy Use (Predicted kWh—Measured kWh)[11]

	HEST	SIMPLE	REM/Rate
Number of Observations	859	859	859
Mean Measured	10,945	10,945	10,945
Mean Predicted	10,309	8,800	11,361
Mean Difference	–636	–2,144	416
Median Difference	–115	–1,514	835
Standard Deviation of Difference	4,443	4,351	4,696
Mean Absolute Difference	3,111	3,326	3,226
Median Absolute Difference	2,424	2,393	2,386
Mean Absolute Percent Difference	33%	30%	35%
Median Absolute Percent Difference	24%	25%	23%
Percent Root Mean Square Error	41%	44%	43%
Percent of Homes < ± 25% Different	54%	49%	52%
Percent of Homes < ± 50% Different	81%	86%	79%
R2 of Regression	0.23	0.26	0.24
Slope of Regression	0.24	0.24	0.39
Intercept of Regression	7,728	6,191	7,053

Table 2. Statistical Summary of Differences Between Predicted and Weather-Normalized Measured NG Use (Predicted Therms—Measured Therms)

	HEST	SIMPLE	REM/Rate
Number of Observations	500	500	500
Mean Measured	871	871	871
Mean Predicted	787	688	1,186
Mean Difference	–84	–183	315
Median Difference	–76	–177	256
Standard Deviation of Difference	342	281	436
Mean Absolute Difference	256	252	392
Median Absolute Difference	193	205	293
Mean Absolute Percent Difference	31%	29%	51%
Median Absolute Percent Difference	24%	27%	37%
Percent Root Mean Square Error	40%	38%	62%
Percent of Homes < ± 25% Different	51%	45%	38%
Percent of Homes < ± 50% Different	83%	89%	60%
R2 of Regression	0.32	0.46	0.40
Slope of Regression	0.53	0.54	0.94
Intercept of Regression	329	217	363

[11] Equations for the statistics presented can be found in Appendix F.

Figure 17 shows a cumulative distribution of percent differences between predicted and weather-normalized measured electric energy use for the three tools evaluated. At the 50% point on the x-axis, the lines cross the median percent difference value on the y-axis. HEST crosses the 50% point at a value of about 1% underprediction, REM/Rate at about 8% overprediction, and SIMPLE about 15% underprediction.

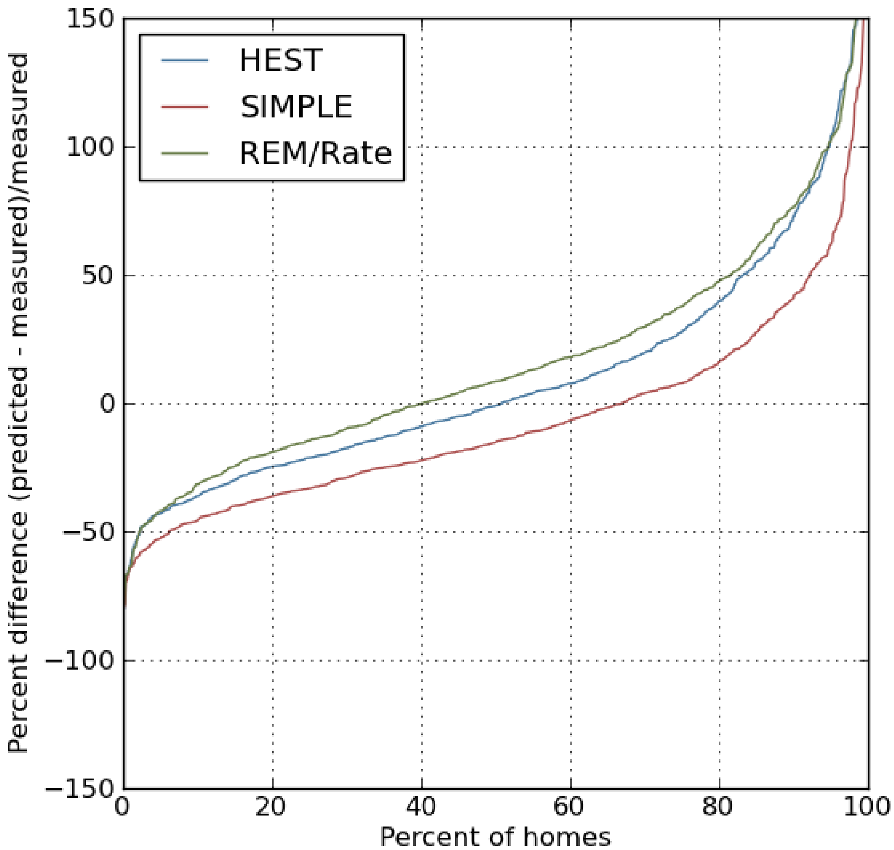

Figure 17. Cumulative distribution plot of percent differences between predicted and weather-normalized measured site electric energy use for the three tools evaluated[12]

Figure 18 shows a cumulative distribution of the percent difference between predicted and weather-normalized measured NG energy use for the tools. One can discern from the distribution that REM/Rate overpredicts NG use for 80% of the homes in the sample, compared to about 40% for HEST and about 25% for SIMPLE.

[12] Data points above 150% difference are not shown on the graph.

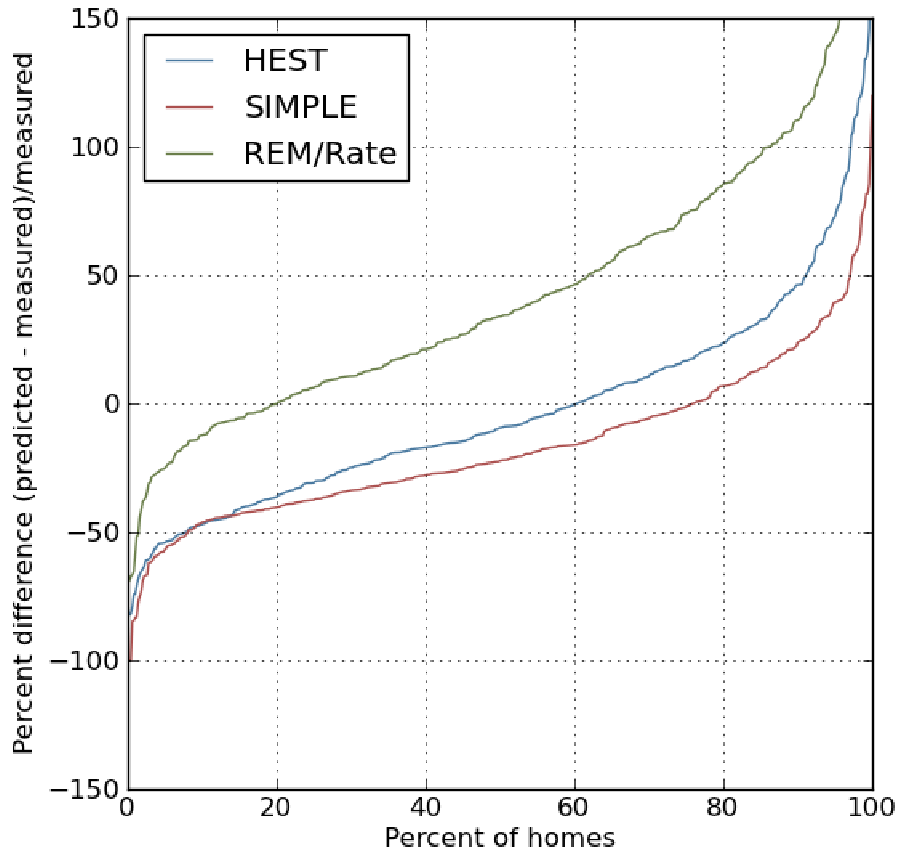

Figure 18. Cumulative distribution plot of percent differences between predicted and weather-normalized measured site NG energy use for the three tools evaluated[13]

[13] Data points above 150% difference are not shown on the graph.

3 Statistical Models

To estimate which inputs contribute the most to differences between HEST predictions and measured energy uses, a statistical analysis approach was applied to the FDR records. More specifically, multiple linear regression (MLR) was used to develop empirical models from HEST inputs and utility billing data. This section covers the approach taken, the resulting models, and what can be concluded from these models.

3.1 Approach

The general model equation for MLR is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon$$

where,

y is the dependent variable

β_0 is the intercept

β_1 through β_n are the coefficients

x_1 through x_n are the independent variables (inputs)

ε is the remaining error.

In MLR, a least-squares-fit algorithm is applied to a dataset that contains multiple records with each record containing one y-value and its associated x-values. Most statistical software programs calculate the coefficients and probability values that allow one to evaluate which coefficients are significant. Polynomial terms (i.e., x_n^2) and interaction terms (i.e., $x_1 x_2$) are sometimes included in the model if they improve the overall fit and have minimal correlation with the other independent variables. Although one starts out initially with a model containing practically all possible independent variables, common practice is to eliminate insignificant variables until a "reduced" model containing only significant variables is achieved.

3.2 Home Energy Score Test Dependent Variables and Inputs

For evaluating HEST results, the following dependent variables were used in four separate empirical models:

- Measured site electricity (weather-normalized)
- Measured site NG (weather-normalized)
- Difference site electricity = (predicted site electricity) – (measured site electricity)
- Difference site NG = (predicted site NG) – (measured site NG).

Separate models for measured site electricity and measured site NG were created to estimate which inputs correlate with measured at a significant level and to evaluate how much variability in the measured results can be explained by these inputs. The next step was to model differences between HEST predictions and measured energy uses. Again, separate models were created for site electricity and site NG. The coefficients from these difference models can be examined to evaluate which HEST inputs correlate with increasing or decreasing difference from measured energy use.

There are approximately 40 HEST inputs. Some, such as floor area, are numeric, but many use DOE-2 codes to describe various types of building construction components (tables for these codes can be found at https://sites.google.com/a/lbl.gov/hes-public/calculation-methodology/appendices/appendix-e). There are separate codes for skylight types, wall types, roof types, foundation types, and many other components that make up a building. For statistical analysis, the frequency of each specific code was examined and then a binary variable was defined for each. More details about variable coding for statistical analysis are given in Section 3.4. An example of a DOE-2 ceiling construction code is "ecwf30," which is defined as 3.5-in. wood ceiling joists @ 24 in. on center (o.c.), 10.5-in. (R-30) fiberglass fill ceiling insulation, and 0.5-in. gypsum wallboard. These construction codes were used in the variable names to allow lookup in the DOE-2 tables for further details. It was desirable to extract insulation R-values from these construction codes because insulation R-values can be treated as numeric variables that likely correlate directly with energy use. For the variable RoofRValue, the R-values were extracted from both "roof" construction codes and "ceiling" construction codes, because often a building had insulation listed for one but not for the other.

3.3 Dataset Limitations and Bias

The current FDR contains measured utility data and HEST building asset characteristics for 1183 homes. The data are limited primarily to five states (Minnesota, North Carolina, Oregon, Texas, and Wisconsin).[14] Only houses that used electric or NG space heating were included in this analysis. To be included, all houses needed to have positive measured electricity use. In addition, houses heated with NG had to have positive measured NG use. This reduced the dataset to 764 homes.

Table 3 lists the number of houses from each historical dataset and state that were included in the statistical analysis. Differences in time periods when data were collected, data collection methods, housing types, and even differences in how the measured utility data were normalized could add variability to the HEST predictions and the measured energy uses. Therefore, each dataset was given its own binary variable and treated the same as any other binary variable in the statistical analysis. The same was done for each state. These particular binaries primarily account for bias error between the individual datasets.

Often the input or explanatory variables from historical datasets are correlated with each other. This can result in distorted estimates of variable coefficients using MLR and cause some insignificant variables to appear significant. MLR models give indications of the most likely inputs that correlate with the dependent variable, but they do not provide absolute certainty.

[14] Three houses from North Carolina Advanced Energy are located in Tennessee. From the 5-digit ZIP code, these houses appear to be located in eastern Tennessee, very near other houses in North Carolina; hence, they are kept in the analysis.

Table 3. Home Count by Historical Datasets and State

Data Set Description[15]	Total Count	State
Building America Audit Assessment	48	Minnesota
EPA ENERGY STAR® Qualified Homes Study	73	Minnesota
EPA ENERGY STAR Qualified Homes Study	1	Wisconsin
Advanced Energy System Vision	255	North Carolina
Advanced Energy System Vision	3	Tennessee
Oregon EPS Study	172	Oregon
Houston Utility Study	42	Texas
Wisconsin Housing Study	170	Wisconsin

In addition to HEST inputs, climate differences are believed to be important. To capture actual climatic differences, two additional independent variables, heating degree days (HDDs) (base 65°F) and cooling degree days (CDDs) (base 65°F), were joined to the dataset and treated as numeric variables. Values for these variables were taken from Typical Meteorological Year (TMY) weather files at weather stations near home locations (based on ZIP code values).

3.4 Variable Coding

All original HEST inputs were coded. These coded inputs became the independent variables in the regression models. Independent variables were coded primarily to allow more meaningful comparison of the coefficients in the final models. The actual coding method depended on whether the variable was numeric or binary. Unless otherwise noted, the numeric variables were coded using a univariate method. Univariate coding is done by subtracting the variable mean and then dividing this difference by the variable standard deviation. The resulting coded variable has a variance of one, hence the term *univariate*. In the few cases where the variable distribution was highly skewed toward zero and the ratio of mean to standard deviation was <1, an alternate coding was used. For the alternate coding, the 95th percentile of the variable was defined as 1 and zero was defined as –1.

With the exception of hot water fuel (hwFuel), the binary variables were coded as Yes = 1 and No = 0. Hot water fuel was coded as Gas = 1 and Electric = –1 to test a possible interaction with the hot water energy factor (hwEnergyFactor). In most cases, the number 1 (or Yes) implies that the particular building has the HEST input characteristic. For example, C_HT_EFN = 1, means the heating type is an electric furnace. Although this is a generally accepted statistical modeling practice, the binary coded variables often have larger coefficients than a univariate coded variable with the same confidence level (CL) as a result of the coding technique. Hence, other statistics from the MLR analysis should be examined to evaluate which variables are most significant.

The binary coding created multiple variables for each categorical input. For example, there were six heating system type categories (electric and NG only). Standard practice is to choose one category as a control. The control has no further variable assignment, as all other categories are

[15] Further description of these datasets can be found in Appendix B.

referenced to the control. New binary variables are created for each of the other categories. Table 4 demonstrates this method for heating types where “gas furnace” is chosen as the control. Not every binary variable is used in the final model, as most do not vary significantly from the control. The resulting number of total variables slightly exceeded 100 (HEST plus state binaries and dataset binaries). A complete list of HEST variables with descriptions is included in Appendix C.

Table 4. Example of Binary Coding for Heating Type Category HEST Input

Heating Type	Description	Record Count	C_HT_EBB	C_HT_EFN	C_HT_EHP	C_HT_GBL	C_HT_GWF
gfn (control)	Gas furnace	471	0	0	0	0	0
ebb	Electric baseboard	10	1	0	0	0	0
efn	Electric furnace	3	0	1	0	0	0
ehp	Electric heat pump	246	0	0	1	0	0
gbl	Gas boiler	27	0	0	0	1	0
gwf	Gas wall furnace	7	0	0	0	0	1

3.5 Models of Measured Energy Use

Approximately 75% of the observations were randomly selected as a model set; the remaining observations were kept as a test set. The model set was used to build the model. The MLR model was then applied to the test set to predict the measured energy use. The R-squared value estimated from the test set (plot of measured versus MLR predicted) can be compared to the R-squared value from the model building process. The R-squared value from the test set does not have to be exactly the same as the R-squared value from the model set, but should be comparable.[16]

Table 5 shows the resulting MLR model with measured site electricity as the dependent variable. All variables listed are significant at a CL ≥95%. The variables highlighted in yellow are significant at a CL >99%. The list is divided between numeric variables and binary and sorted from most significant to least significant within each variable type. An adjusted R-squared value of 0.433 resulted; this implies that the model can explain approximately 43% of the observed variability in measured electricity use.

[16] There are no specific rules, but from experience, if the adjusted R-squared value for the model set exceeds the adjusted R-squared value for the test set by more than 0.1, the model set has likely not captured the most significant factors.

Table 5. Significant Model Variables and Coefficients for Measured Site Electricity

Variable Type	Model Variable	Original Variable Description	Coefficients (MMBtu)	CL From MLR
	(Intercept)		32.4	100.0%
Numeric	C_numberBedrooms	Number of bedrooms	3.8	100.0%
Numeric	C_floorArea	Floor area (ft^2)	5.2	100.0%
Numeric	C_W_WindowArea	Western facing window area (ft^2)	1.4	98.5%
Binary	C_HT_EHP	Heating type EHP (electric heat pump)	17.5	100.0%
Binary	C_HT_EBB	Heating type EBB (electric baseboard)	25.2	100.0%
Binary	C_HT_EFN	Heating type EFN (electric furnace)	41.7	100.0%
Binary	State_MN	State of Minnesota	–6.3	100.0%
Binary	C_hwFuel	Hot water fuel type (gas or electric)	–3.4	100.0%
Binary	C_WC_ewps19wo	Wall construction code ewps19wo (0.5-in lapped wood siding, 0.5-in fiberboard sheathing, 5.5-in. wood studs @ 16 in. o.c., 1-in. expanded polystyrene, R-19 mineral fiber batt insulation, 0.5-in. gypsum wallboard)	–7.7	98.2%

Figure 19 shows a graph of the measured site electricity for the model set versus the MLR prediction and a graph of the test set where the resulting MLR model is used to make predictions. When linear regression is applied on the measured site electricity versus the MLR predicted site electricity for the test set, an adjusted R-squared value of 0.343 results. The test set results in an adjusted R-square that is comparable to the model adjusted R-square and the plot of measured energy use from the test set has a pattern similar to the plot of measured from the model set, confirming the MLR model's predictive capability for this dataset. The coefficients will likely change as more data become available in the FDR. Nevertheless, the most significant coefficients appear to be understandable. For example, increased electricity use with increased number of bedrooms is indicated in the model and might be due to more occupants using more electricity. A positive coefficient for floor area might follow from similar factors. Using gas for hot water fuel should decrease electricity use, hence the negative coefficient. Increased electricity use is expected when electric baseboard, electric furnace, or electric heat pump are used.

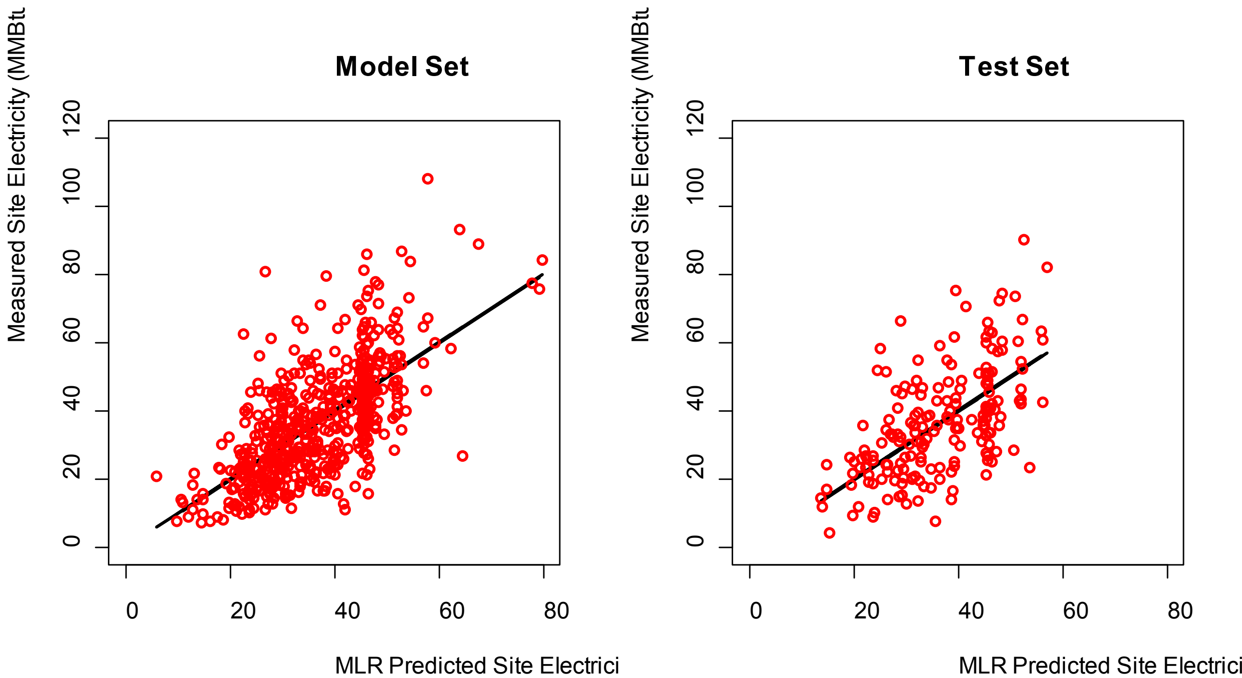

Figure 19. Measured versus MLR-predicted site electricity for the model set (left) and test set (right)

Minnesota appears to have significantly lower electricity use than other states in the dataset. Both Minnesota datasets showed similar bias. Because of the limited number of datasets, one cannot conclude at this time that Minnesota is truly different. The Minnesota variable correlates strongly (R values greater than 0.5) with both ceiling construction using R-49 insulation and wall construction using R-19 insulation. The same level of correlation for these inputs was not observed for other states. As data are collected for Minnesota homes with less insulation, these construction inputs may become significant.

For modeling measured site NG, only buildings where NG is used for space heating were included. This reduced the number of observations to 505. As with the electric model, these observations were further divided into a model set (about 75% randomly selected) and a test set (the remainder).

Table 6 shows the resulting MLR model with measured site NG as the dependent variable. The resulting adjusted R-squared for this model is 0.650, which indicates that the model explains 65% of the variability. Graphs in Figure 20 show measured site NG versus MLR-predicted site NG, with the test set graph showing a pattern similar to the model set graph. At least some of the model variable coefficients appear to agree with how the input might be expected to influence NG use. For example, houses in locations with more HDDs would be expected to use more NG for space heating. Increased air leakage and increased floor area both contribute to higher NG use. A gas furnace with higher efficiency reduces NG use. Some variables do not make sense and may be artifacts of the current available data. In particular, age in years indicates a reduction in NG use for older buildings. Age in years correlates strongly with the Oregon dataset. As older homes in other states are added to the FDR, a better test should result for the age in years variable.

Table 6. Significant Model Variables and Coefficients for Measured Site NG

Variable Type	Model Variable	Original Variable Description	Coefficients (MMBtu)	CL from MLR
	(Intercept)		78.1	100.0%
Numeric	C_HDD_65F	HDDs (base 65°F)	20.8	100.0%
Numeric	C_airLeakage50ip	Air leakage (cfm)	8.8	100.0%
Numeric	C_heatingEfficiency	Heating efficiency for home heating system	–24.9	100.0%
Numeric	C_floorArea	Floor area (ft^2)	7.0	100.0%
Numeric	C_E_WindowArea	Eastern facing window area (ft^2)	5.1	99.9%
Numeric	C_age_years	House age in years	–5.9	99.9%
Numeric	C_N_WindowArea	Northern facing window area (ft^2)	4.3	99.7%
Numeric	C_WASG_Total	sum((Window area) × (solar heat gain coefficient [SHGC]))	5.5	99.3%
Numeric	C_houseOrientation	House orientation (0 = N, 90 = E, 180 = S, and 270 = W)	–3.8	98.9%
Binary	C_hwFuel	Hot water fuel type (gas or electric)	8.7	100.0%
Binary	C_FC_efwf30ca	Floor construction code efwf30ca (11.5-in wood joists @ 24 in. o.c., R-30 mineral fiber batt insulation, 0.75-in. wood underlayment, 0.75-in. wood subfloor, carpeting)	–39.7	99.7%
Binary	C_FC_efwf25ca	Floor construction code efwf30ca (11.5-in. wood joists @ 24 in. o.c., R-25 mineral fiber batt insulation, 0.75-in. wood underlayment, 0.75-in. wood subfloor, carpeting)	–16.1	99.7%

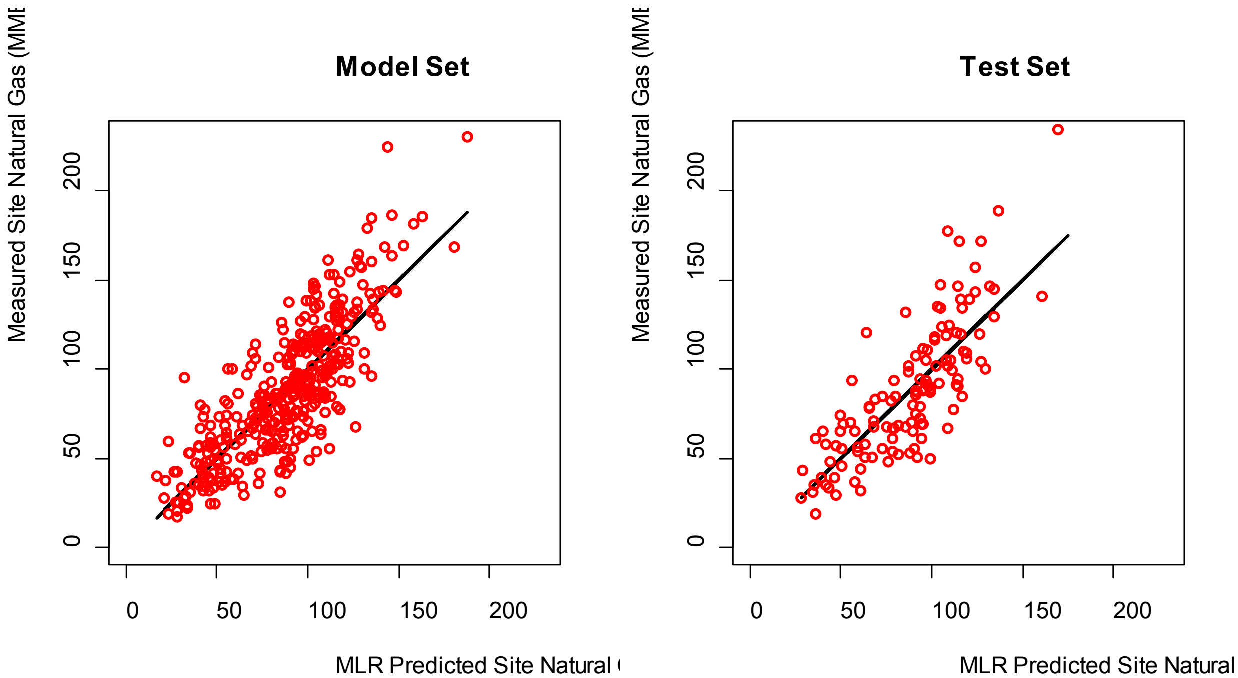

Figure 20. Measured versus MLR-predicted site NG for model set (left) and test set (right)

3.6 Models of Differences Between Predicted and Measured Energy Uses

Table 7 shows the resulting MLR model with difference site electricity as the dependent variable. Again, the difference is predicted site electricity minus measured site electricity. The resulting adjusted R-squared value for this model is 0.199, which indicates that only about 20% of the variability in the differences can be explained by this model. Seven variables listed are significant at CLs ≥ 99% and three other variables are significant at 95% CL. Additional validation was done by combining the MLR prediction for measured site electricity with the MLR prediction for the difference model. Plotting the combined MLR prediction versus the measured site electricity shows a pattern very similar to the HEST predictions (see Appendix E).

Table 7. Significant Model Variables and Coefficients for Difference Site Electricity

Variable Type	Model Variable	Original Variable Description	Coefficients (MMBtu)	CL from MLR
	(Intercept)		–1.2	85.5%
Numeric	C_numberBedrooms	Number of bedrooms	–3.3	100.0%
Numeric	C_floorArea	Floor area (ft^2)	2.4	99.7%
Numeric	C_WallRValue	Wall R-value determined from wall construction inputs	–1.7	99.6%
Binary	C_HT_EFN	Heating type EFN (electric furnace)	26.9	100.0%
Binary	C_CT_ehp	Cooling type ehp (electric heat pump)	–5.1	99.9%
Binary	C_ST_dseab	Skylight type dseab (double-pane, low-solar-gain low-E (e = 0.05 on surface 2, aluminum spacer and frame with thermal break)	–18.4	99.5%
Binary	State_MN	State of Minnesota	4.7	99.5%
Binary	C_WC_ewps19wo	Wall construction code ewps19wo (0.5-in. lapped wood siding, 0.5-in. fiberboard sheathing, 5.5-in. wood studs @ 16 in. o.c., 1-in. expanded polystyrene, R-19 mineral fiber batt insulation, 0.5-in. gypsum wallboard)	9.1	98.9%
Binary	C_HT_EBB	Heating type EBB (electric baseboard)	9.6	97.1%
Binary	C_CC_ecwf21	Ceiling construction code ecwf21 (3.5-in. wood ceiling joists @ 25 in. o.c., R-21 fiberglass fill ceiling insulation, 0.5-in. gypsum wallboard)	8.1	96.7%

The coefficients give a magnitude estimate and sign for each variable. The very low R-squared values indicate that only a fraction of the difference between HEST-predicted and measured values can be explained by the inputs. Nevertheless, a few variables might be worth investigating. At least six of the significant variables in the difference site electricity model occur in the measured site electricity model. The negative coefficients for number of bedrooms, wall R-value, and a few other variables indicate that the difference decreases as these variables increase. The positive coefficients for variables such as floor area, electric furnace, and the R-19 wall construction indicate that the difference increases as these variables increase.

Table 8 shows the resulting MLR model with difference site NG as the dependent variable. The resulting adjusted R-squared value for this model is 0.456, which indicates that about 46% of the variability in the difference can be explained by this model. All variables listed are significant at a CL ≥ 95%. Seven numeric variables plus three binary variables are significant at a CL > 99%.

Table 8. Significant Model Variables and Coefficients for Difference Site NG

Variable Type	Model Variable	Original Variable Description	Coefficients (MMBtu)	CL from MLR
	(Intercept)		9.8	97.7%
Numeric	C_HDD_65F	HDDs (base 65°F)	7.5	100.0%
Numeric	C_E_WASG	(East window area) × (SHGC)	–6.7	100.0%
Numeric	C_heatingEfficiency	Heating efficiency for home heating system	–23.8	100.0%
Numeric	C_RoofRValue	Roof R-value determined from roof construction and ceiling construction inputs	–5.5	100.0%
Numeric	C_N_WindowArea	North-facing window area (ft^2)	–4.2	99.8%
Numeric	C_houseOrientation	House orientation (0 = N, 90 = E, 180 = S, and 270 = W)	4.5	99.7%
Numeric	C_airLeakage50ip	Air leakage (cfm)	4.4	99.4%
Numeric	C_age_years	House age in years	4.3	97.4%
Binary	C_WC_ewwf00wo	Wall construction code ewwf00wo (0.5-in. lapped wood siding, 0.5-in. fiberboard sheathing, 3.5-in. wood studs @ 16 in. o.c., 3.5-in. vertical air spaces (no insulation), 0.5-in. gypsum wallboard)	16.9	100.0%
Binary	C_HT_GBL	Heating type GBL (gas boiler)	26.6	100.0%
Binary	C_WC_ewwf19wo	Wall construction code ewwf19wo (0.5-in. lapped wood siding, 0.5-in. fiberboard sheathing, 5.5-in. wood studs @ 16 in. o.c., R-19 mineral fiber batt insulation, 0.5-in. gypsum wallboard)	–13.5	99.7%

HDDs were significant for both the measured site NG and the difference model. Both had positive coefficients. The indication is that HEST overpredicts the impact of greater HDDs, perhaps for a variety of reasons: the assumed heating set point may be too high, the variation in indoor air temperature is too great, empty wall cavities are imperfectly modeled, etc. Air leakage also had positive coefficients for both models. Increased air leakage increases energy use, but HEST might be overpredicting the impact.

Heating efficiency was significant for both the measured site NG and the difference model, but had negative coefficients. The measured site NG model shows a reasonable trend, declining NG use as the heating system efficiency increases. The negative estimate for the difference model indicates that HEST may not completely capture the impact of increasing system efficiency.

The roof R-value was not significant in the measured site NG model, but is significant in the difference model. One would expect that as roof R-value increases, the NG use should decrease, but it might be that in actuality NG use does not decrease as much as HEST predicts. Hence the predicted would be less than the measured.

A few other variables had interesting trends. Increased age in years showed lower NG use. The difference model indicated a possible overprediction by HEST. This might be an artifact of limited data. One generally expects newer homes to use less energy, but on average the newer homes have more floor area. Increasing north- and east-facing window area correlates with increasing NG use. The difference model indicated underprediction by HEST for at least the north-facing window area. House orientation indicated lower NG use as the orientation moved away from being directly north (0 angle). The difference model indicated a possible overprediction by HEST for orientation.

The binary variables are sometimes more difficult to explain. The difference model indicates that HEST overpredicted NG use for homes with wood frame wall construction with no insulation (ewwf00wo). This could be due to lower average indoor temperatures caused by zoning or inaccurate modeling of uninsulated walls. One would expect higher energy use with less wall insulation, but in this case the correlation with wall construction types with low insulation did not prove significant in the measured NG model and might be hidden due to other sources of variability. Wall R-values were also estimated based on the DOE-2 wall construction codes and tested separately, but did not prove to be significant. Two floor construction types with R-30 and R-25 insulation (efwf30ca and efwf25ca) correlated with reduction in measured NG use. Lower differences were observed for homes with another type of wall construction (ewwf19wo designates wood frame construction with R-19 mineral fiber batt insulation in the wall).

3.7 Summary

In spite of the data limitations, MLR models indicated significant correlations between measured energy use and several HEST inputs. These methods also indicated significant correlations between differences (HEST predicted minus measured energy use) and several HEST inputs. How these inputs were collected and used in the HEST prediction models can be investigated to identify causes for differences from measured energy use and potential improvements to software inputs and models.

The statistical models discussed in this section apply only to the current FDR data used to develop the models. As more data are collected, it is likely that the coefficients will change, new inputs will become significant, and current significant inputs might prove to be insignificant. Nevertheless, the current statistical models identified several HEST inputs that significantly correlated to measured site energy use (both electricity and NG). The difference models identified HEST inputs that correlated with increasing or decreasing difference from measured energy use. These inputs might be causing the differences or they might be used in models or algorithms that are causing the differences.

4 Operational Uncertainty Analysis

The Home Energy Score assesses the performance of the energy-related assets of a home under typical operating conditions (standard occupants). However, utility billing data reflect the performance of the energy-related assets of a home under actual operating conditions, which can vary greatly. Therefore, when assuming standard occupancy, there is considerable uncertainty that predictions will agree with utility billing data because actual occupant behavior is not considered. The goal of this analysis was to estimate the effect of operational input uncertainty on the uncertainty in energy use predictions. A development version of BEopt™/EnergyPlus[17] was used to perform the simulations.

4.1 Approach

Two prototypical houses were utilized in the analysis:[18]

- House A: 1,539-ft^2, one-story, detached, inefficient home, representative of 1960s-era construction.
- House B: 2,500-ft^2, two-story, detached, more efficient home, representative of new construction.

The following technical approach was used to estimate the effect of operational input uncertainty on the uncertainty in energy use predictions:

1. Identify operational inputs accessible in the BEopt input file and select a subset of key inputs for variation.
2. Define probability distributions representing the uncertainty ranges for each key input.
3. Randomly select values from probability distributions for each key input and simulate energy use for that realization of inputs.
4. Repeat Step 3 for many realizations to generate a range of simulation output.
5. Analyze the distributions of simulated energy uses.

Nineteen inputs related to the operation of the homes were selected for this analysis. These inputs, their physical units, and key notes are listed in Table 9.

.

[17]The BEopt (Building Energy Optimization) software was developed by NREL to evaluate residential building designs. The software can be used to analyze both new construction and existing home retrofits, and provides detailed analysis using house characteristics. The version of BEopt used in this analysis utilizes the EnergyPlus building energy simulation engine. EnergyPlus has been developed and supported by DOE Building Technologies Program since 1996.

[18] More information about the operational uncertainty analysis and assumed features of the homes can be found in Polly (2011).

Table 9. Operational Inputs Perturbed in Monte Carlo Simulations

General Category	Input(s)	Units	Notes
Thermostat	Heating set point	°F	All hours during the weekday and all hours during the weekend were set to the same value.
	Cooling set point	°F	All hours during the weekday and all hours during the weekend were set to the same value.
Miscellaneous Electric Loads (MELs)	MELs multiplier	–	MELs include all plug loads and loads not explicitly defined in the Major Appliances group. Multiplier values specify a fraction of the Building America House Simulation Protocols (HSP) energy use.
Miscellaneous Gas Loads (MGLs)	MGLs multiplier		MGLs include all gas loads not expressly defined in the Major Appliances group, such as gas fireplaces, grills, and pool heaters. Multiplier values specify a fraction of the HSP energy use.
Miscellaneous Hot Water Loads	Sink multiplier, shower multiplier, bath multiplier.	–	Sinks, Showers, and Baths water use (other water use is handled in the appliance group). Multiplier values specify a fraction of the HSP hot water consumption.
Interior Shading	Heating shade multiplier, cooling shade multiplier.	–	Interior shading multiplier for heating and cooling seasons. Solar gains through windows are reduced by the Interior Shading multipliers.
Lighting	HSP interior/exterior lighting energy multipliers	kWh/yr	Multiplier values specify a fraction of the HSP annual lighting energy use.
Furniture	Conductivity	Btu-in./h·ft^2·°F	Conductivity of furnishings.
	Density	lb/ft^3	Density of furnishings.
	Specific heat	Btu/lb·°F	Specific heat of furnishings.
	Area fraction	–	Fraction of finished floor area covered by furniture.
	Weight	lb/ft^2	Furniture mass per finished floor area.
	Solar absorptance	–	Solar absorptance of furnishings.
Refrigerator	HSP multiplier	–	Multiplier values specify a fraction of the HSP electric energy use.
Electric Range and Dishwasher	HSP multipliers	–	Multiplier values specify a fraction of the HSP electric energy and hot water use.
Clothes Washer and Electric Clothes Dryer	HSP multipliers	–	Multiplier values specify a fraction of the HSP electric energy and hot water use.
Natural Ventilation	Fraction of total window area open	–	Specifies the fraction of total window area that is open during natural ventilation.
Water Heater	Water heater set point	°F	Water heater set point temperature.

Input values were randomly selected from triangular probability distributions. For this distribution the probability of selection is greatest at the nominal value and decreases linearly to zero at the minimum and maximum values. The triangular distribution may be either symmetric or asymmetric with respect to the nominal value; an asymmetrical distribution is shown in Figure

21. Table 10 shows the minimum, nominal, and maximum values used to define the triangular probability distributions for the 19 inputs. Values were chosen using engineering judgment considering previous work by a group of industry experts to define uncertainty ranges for the Building Energy Simulation Test for Existing Homes (BESTEST-EX) (Judkoff et al. 2010).

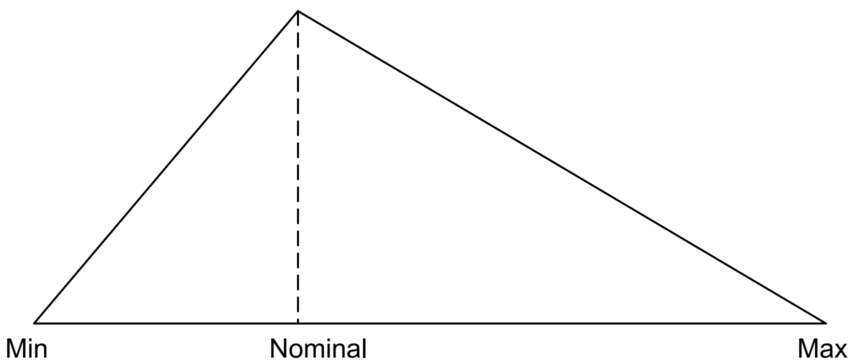

Figure 21. Triangular probability distribution used for input selection

Table 10. Perturbed Operational Inputs and Associated Uncertainty Ranges

Input	Minimum	Nominal	Maximum
Space Heating Set Point (°F)	60	68	75
Space Cooling Set Point[19] (°F)	71	78	86
MELs Multiplier	0.2	0.8	2.0
MGLs Multiplier	0.2	0.8	2.0
Miscellaneous Hot Water Loads Multiplier	0.2	0.8	2.0
Interior Shading Multiplier	0.5	0.6	1.0
Interior Lighting Multiplier	0.2	0.8	2.0
Exterior Lighting Multiplier	0.2	0.8	2.0
Furniture Conductivity (Btu·in./h·ft^2·°F)	0.64	0.80	0.96
Furniture Density (lb/ft^3)	32	40	48
Furniture Specific Heat (Btu/lb·°F)	0.232	0.290	0.348
Furniture Area Fraction	0.1	0.3	0.5
Furniture Weight (lb/ft^2)	2	8	14
Furniture Solar Absorptance	0.4	0.6	0.8
Refrigerator Multiplier	0.7	1.0	1.3
Range/Dishwasher Multiplier	0.2	0.8	2.0
Clothes Washer/Dryer Multiplier	0.2	0.8	2.0
Fraction of Total Window Area Open	0.00	0.04	0.14
Water Heater Set Point (°F)	110	125	140

[19] The thermostat model in BEopt/EnergyPlus does not allow the heating set point to be greater than the cooling set point. The small percentage of realizations where this occurred was excluded from the analysis.

4.2 Results

For this analysis, approximately 2500 realizations of inputs values were randomly selected and simulated in BEopt/EnergyPlus for both House A and House B. Figure 22 shows annual total source energy use output distributions in Chicago, Illinois for House A and House B. The dashed lines are normal distributions based on the output sample mean and sample standard deviation. For both House A and House B, the SD is equal to approximately 11% of the mean (i.e., the coefficient of variation (COV) = SD/Mean = 0.11).

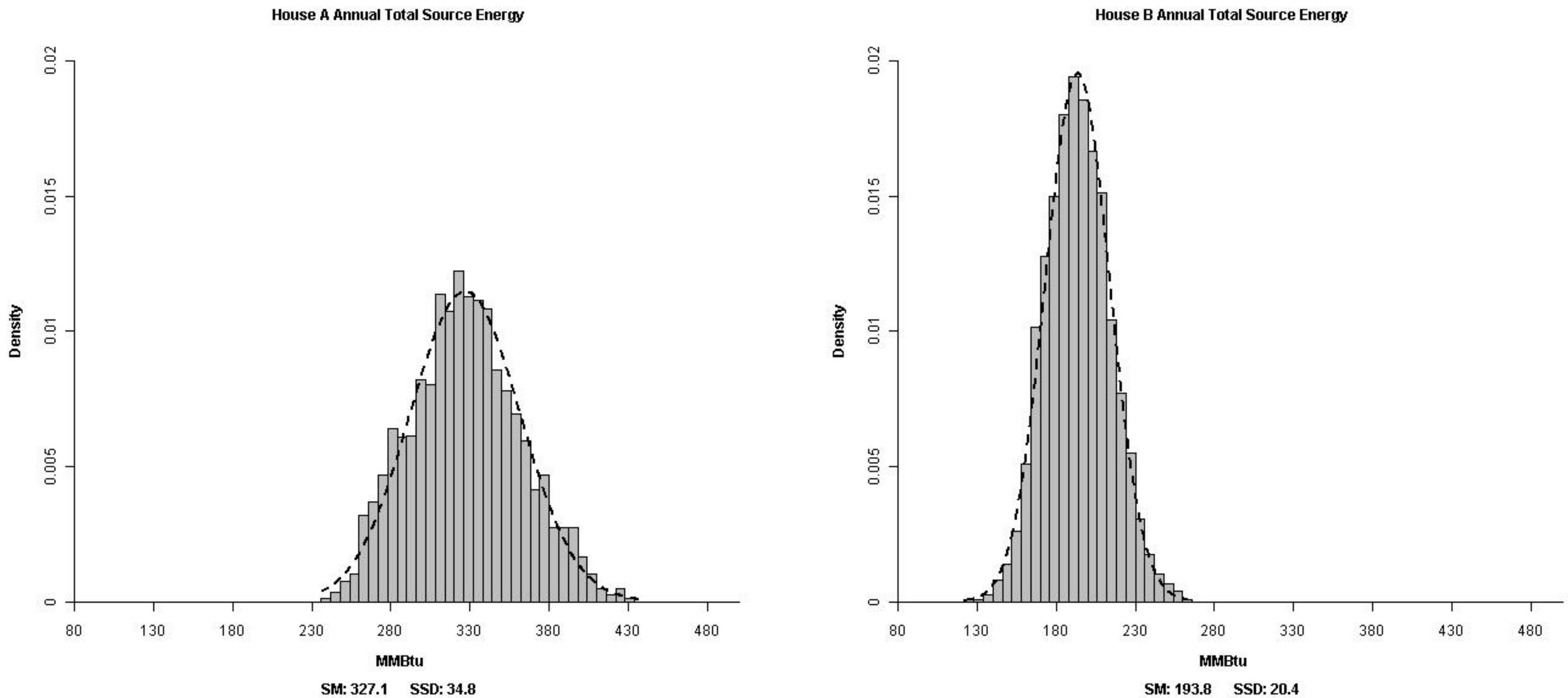

Figure 22. Annual total source energy output distributions in Chicago, Illinois

Similar uncertainty analyses were undertaken for other U.S. cities as shown in Table 11. Three key takeaways are:

- The COV varies by 0.03 or less between the prototypical houses.
- The COV varies by 0.07 or less (House A) and 0.05 or less (House B) across climates—occupants seem to have greater impact on the total energy use of the homes in milder climates.
- Overall, the analysis shows that even if all other sources of inaccuracy are eliminated in an asset analysis, differences between software predictions and measured source energy could be significant because occupant behavior is variable relative to standard assumptions. For example, simulations showed total source energy use differences of up to 36%.[20]

Table 11. Mean, SD, and COV for Total Source Energy Use (MMBtu/yr) by Climate

	HOUSE A			HOUSE B		
	MEAN	**SD**	**COV**	**MEAN**	**SD**	**COV**
Atlanta, Georgia	212.2	27.4	0.13	146.5	19.8	0.14
Chicago, Illinois	327.1	34.8	0.11	193.8	20.4	0.11
Houston, Texas	192.5	26.8	0.14	142.9	21.2	0.15
Los Angeles, California	129.5	22.9	0.18	111.4	18.1	0.16
Phoenix, Arizona	228.7	30.5	0.13	157.6	22.4	0.14
Seattle, Washington	233.6	37.5	0.16	148.7	19.4	0.13
City Average	**220.6**	**30.0**	**0.14**	**150.1**	**20.2**	**0.14**

4.3 Applying Uncertainty Analysis Results to FDR Comparisons

Figure 23 compares the results of the operational uncertainty analysis to the results from the HEST comparative analyses in Section 3.1. The gray distribution shows the differences between HEST predictions and measured energy uses in the FDR.[21] These differences are the result of all sources of inaccuracy, including inaccuracies in inputs related to the occupants, the asset, and the site. The overlaid blue distribution represents the predicted differences caused by occupant variability relative to standard assumptions.[22] The assumption of standard occupancy is necessary to provide an assessment of the home's energy performance that can be fairly compared to assessments of the energy performance of other homes under the same standard conditions. As seen in Figure 23, occupant variability is a very significant source of inaccuracy, but does not explain all of the differences observed in the FDR comparisons. The remaining sources of inaccuracy could be targeted to improve HEST. For example, assessment procedures

[20] The 36% value corresponds to two standard deviations in the Los Angeles climate and roughly bounds 95% of the differences.
[21] The comparative analyses in Section 3.1 cover site electricity and natural gas. Total source energy use differences are discussed in Section 6.2.
[22] A COV value of 0.14 was used generate occupant variability plot. To simplify the presentation, differences are shifted so the mean difference is zero for each distribution.

may be adjusted considering tradeoffs in accuracy, cost, and time necessary to perform the assessment.

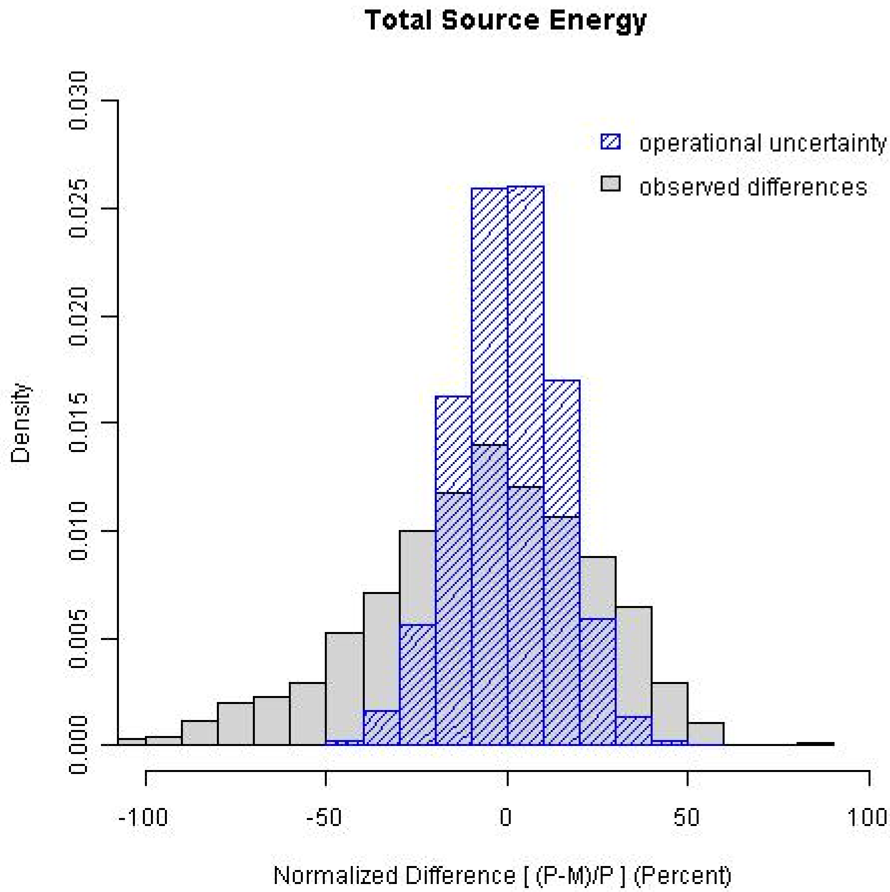

Figure 23. Predicted differences due to operational uncertainty overlaid on observed differences from FDR comparisons

5 Sensitivity to Assessment of Whole-House Leakage

HEST accepts either a quantitative measurement of whole-house leakage using a blower door or a qualitative assessment of whether the home as been air sealed.[23] When a user enters the quantitative results of a blower door test in CFM50, the software uses this datum to calculate the leakage area of the home, a direct input into the underlying DOE-2 infiltration model. When a user enters the qualitative assessment, HEST estimates from historical data the leakage area of the home based on this input and a few other key parameters.[24]

5.1 Approach

During the Home Energy Score pilot, blower door measurements were collected for 655 homes. NREL reran these homes through HEST. Each home was run three times using different inputs for whole-house air leakage:[25]

- Using the blower door data (CFM50)
- Using the qualitative assessment of "sealed"
- Using the qualitative assessment of "unsealed"

5.2 Results

Results of these runs are presented in Figure 24 and Figure 25. The figures compare the total predicted source energy from HEST using the two qualitative input values to the total predicted source energy from HEST using the quantitative input stemming from a blower door measurement.

[23] The quantitative input is entered as cubic feet per minute at 50 Pascals of pressure (CFM50). The qualitative input is choosing *Yes* or *No* to the question *Does the house have weather-stripping and/or caulking to prevent air leakage?* The HESpro website help tip for the qualitative input reads as follows: *Answer "no" unless there has been a specific effort to stop all air leaks in the home within the last two years.*
[24] Details about the HES infiltration model can be found in the HES engineering documentation, available online at https://sites.google.com/a/lbl.gov/hes-public/.
[25] For the 655 homes in which blower door data were collected, only 12 have data about a qualitative assessment of whole-house air leakage. Additionally, assessors who conducted the blower door test also provided the qualitative input and one must assume the diagnostic test results influenced the qualitative assessment. Hence, for this analysis we chose to include both *Sealed* and *Unsealed* results for each home.

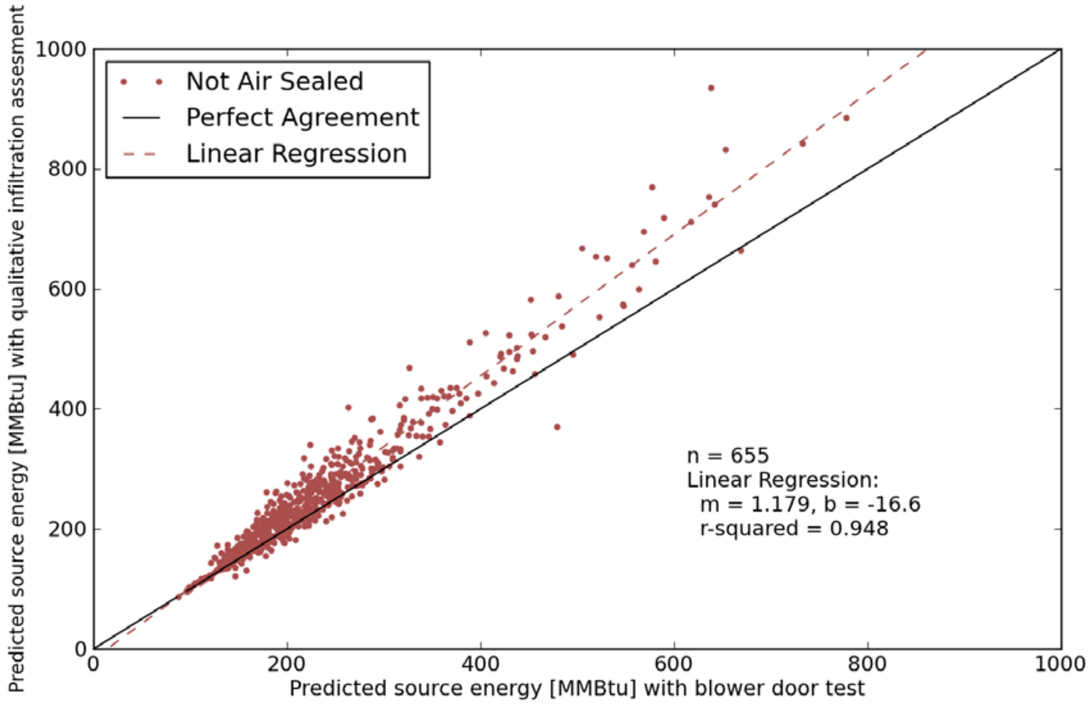

Figure 24. Predicted source energy use from HEST using unsealed qualitative input for whole-house air leakage versus quantitative whole-house leakage

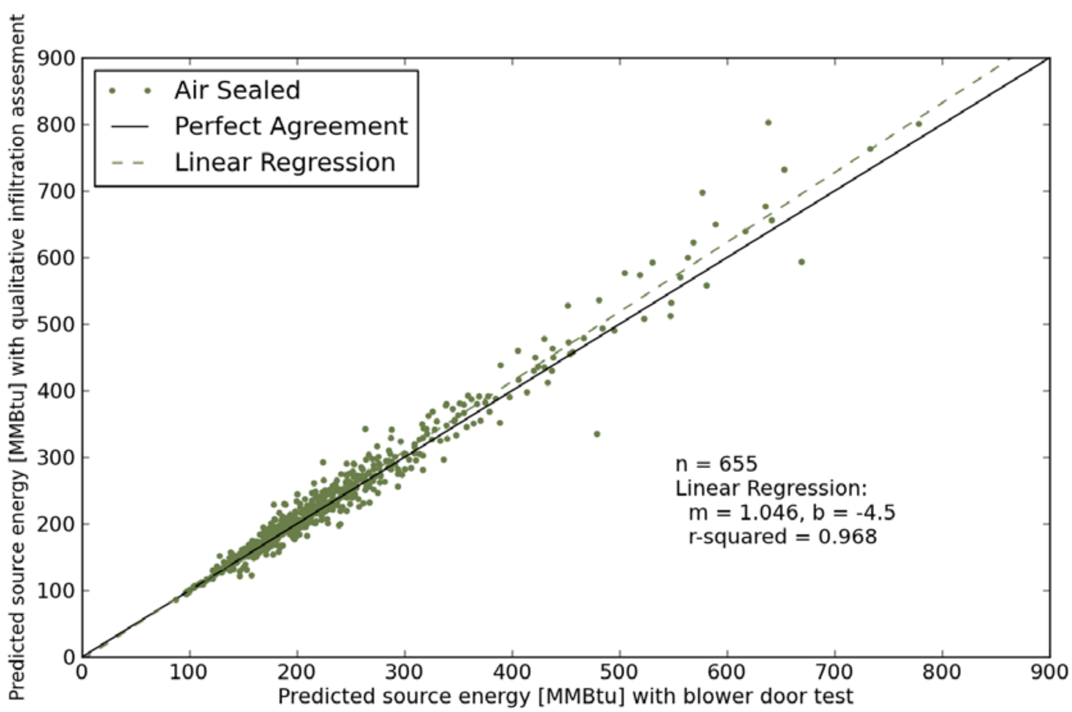

Figure 25. Predicted source energy use from HEST using sealed qualitative input for whole-house air leakage versus quantitative whole-house leakage

Figure 26 shows the frequency distribution of the predicted annual source energy use using the three variations in whole-house leakage input.

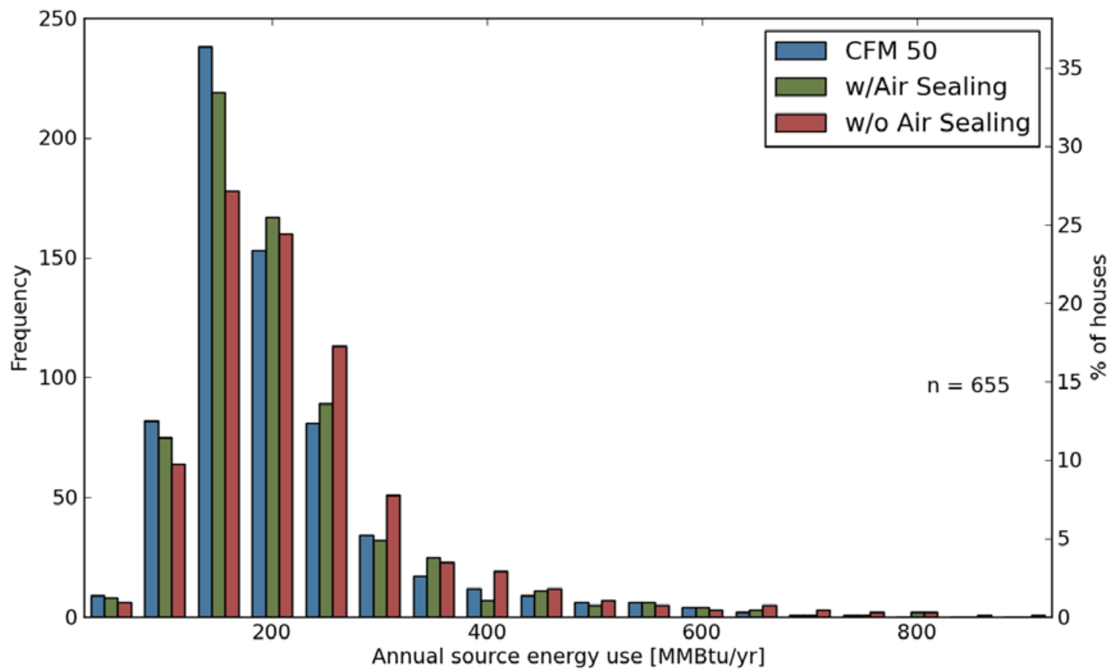

Figure 26. Distribution of HEST-predicted source energy use for 655 homes generated using three different input scenarios for whole-house leakage

Table 12 shows the average value of the source energy for each of the three whole-house infiltration input scenarios. Note that the mean source energy use is lower using the measured whole-house leakage than for either of the qualitative input values. It appears that, on average, the measured air leakage for the homes in this sample is slightly lower than the default leakage estimated by HEST.

Table 12. Average HEST-Predicted Source Energy Use for Each of Three Input Scenarios for Whole-House Infiltration

	CFM50	Sealed	Unsealed
Mean Source Energy (MMBtu/yr)	227	233	251

Figure 27 shows the difference in predicted source energy use generated by HEST using the quantitative and qualitative inputs for whole-house air infiltration. On average, when compared to the predictions stemming from quantitative input, the source energy use is increased by 6 MMBtu/yr when the sealed qualitative input is used and by 24 MMBtu/yr when the unsealed qualitative input is used. This could indicate that the assumptions behind the qualitative inputs cause overestimation of leakage area.

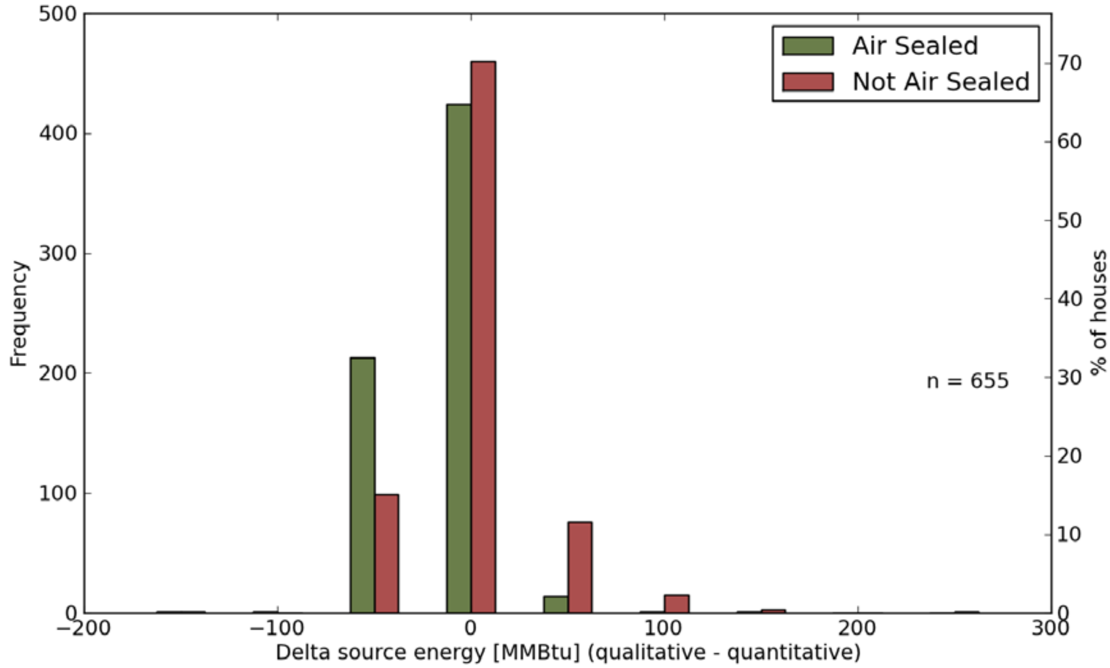

Figure 27. Distribution of differences in home energy score-predicted source energy use using qualitative and quantitative input for whole-house leakage

Additional analysis examining sensitivity in terms of the Home Energy Score to the quantitative and qualitative inputs for whole-house air infiltration is presented in Section 6.3.

6 The Score

The primary objective of the Home Energy Score program is to issue a score to the homeowner. Although the details of the score calculation were in flux throughout the period in which NREL conducted this analysis, the results reflect the scoring bins released by DOE on May 19, 2012.

6.1 Calculation of Score

The Home Energy Score is calculated from total source energy consumption for the home as predicted in HEST. The source energy predictions are transformed into scores based on 10-point bins of source energy that have been established for 245 TMY climate stations. Glickman (2012) provides a detailed description of the development of the scoring bins.

6.2 Predicted Score Versus Score Calculated From Measured Data

Figure 28 shows the relationship between predicted source energy use from HEST and weather-normalized measured source energy use for the homes in the FDR. Figure 29 shows the distribution of differences between the HEST source energy predictions and the weather-normalized measured source energy use. HEST does a good job on average of predicting total source energy, with a median difference between predicted and measured energy use of just 8 MMBtu/yr, or about 0.4%.

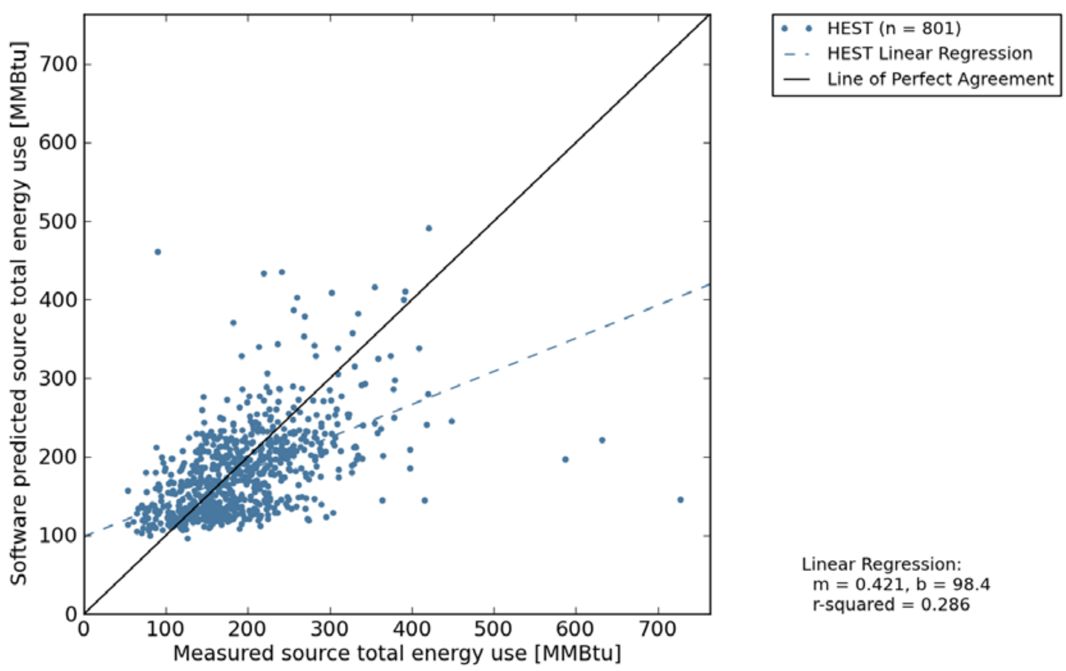

Figure 28. HEST-predicted source energy use versus weather-normalized measured source energy use

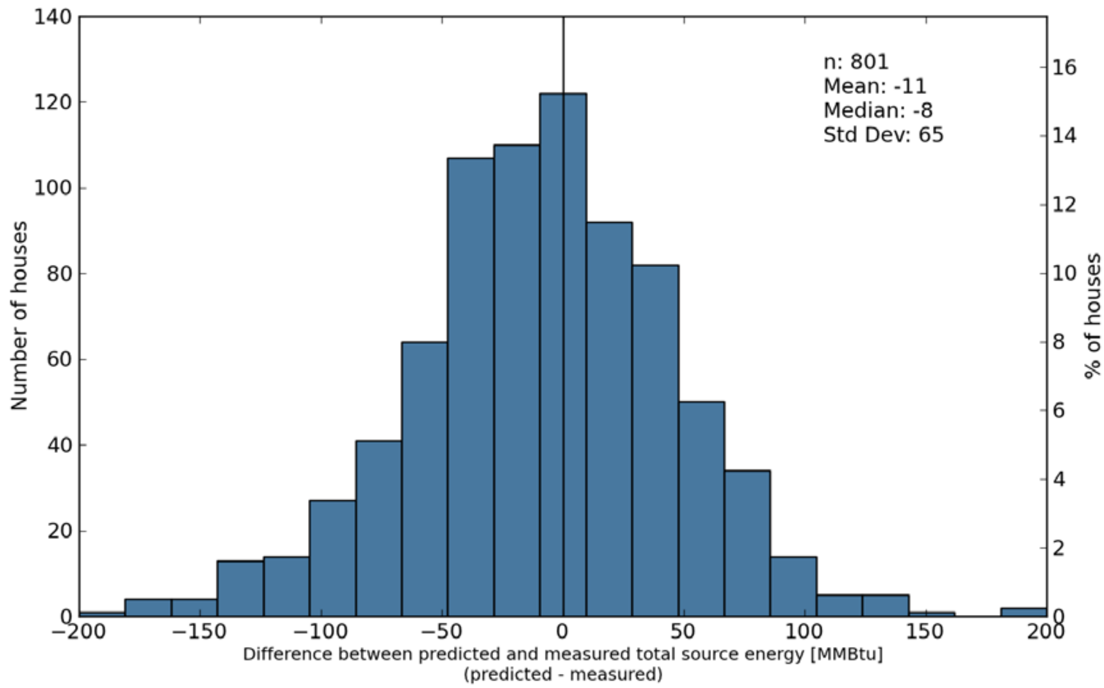

Figure 29. Distribution of differences between HEST-predicted and measured source energy use

Figure 30 shows the cumulative distribution of differences between HEST-predicted and measured source energy use. The median difference between predicted and measured source energy use is –8 MMBtu/yr; this can be observed at the 50% point on the x-axis in Figure 30. It can also be observed in Figure 30 that HEST underpredicts source energy use in about 60% of the homes.

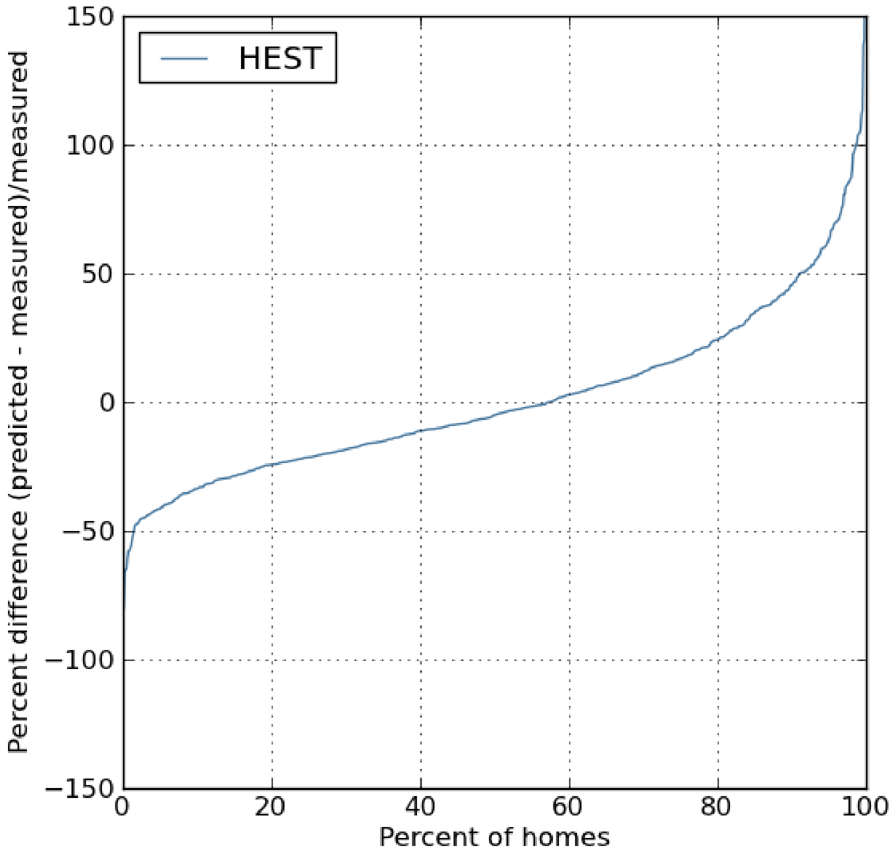

Figure 30. Cumulative distribution of differences between HEST-predicted and measured source energy use[26]

Figure 31 is a bubble graph of the HEST-calculated score versus a score calculated from the weather-normalized measured source energy use for the homes in the FDR. The size of each bubble represents the number of occurrences at that point. The number of occurrences is also displayed numerically inside or alongside each bubble. The axes are inverted to make this figure comparable to those above; lower scores represent higher energy use.

[26] Data points above 150% difference are not shown on the graph.

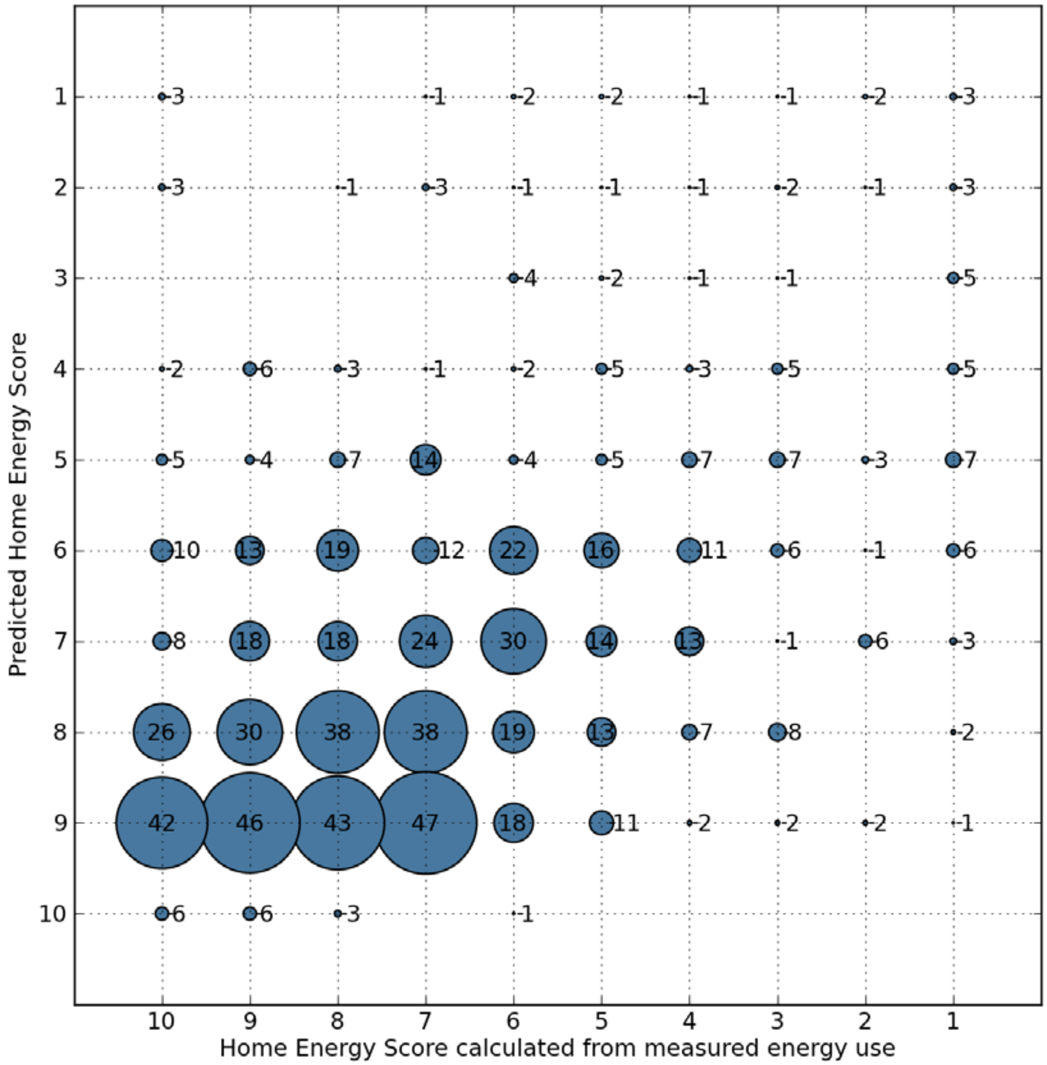

Figure 31. Predicted score versus score calculated from weather-normalized measured source energy use

Figure 32 shows a histogram of the differences between the HEST-calculated score and the score calculated from measured data. The mean and standard deviation of the differences are shown in the figure. For 52% of the homes in this sample, the predicted HEST is within ±1 point of a score calculated from measured energy use.

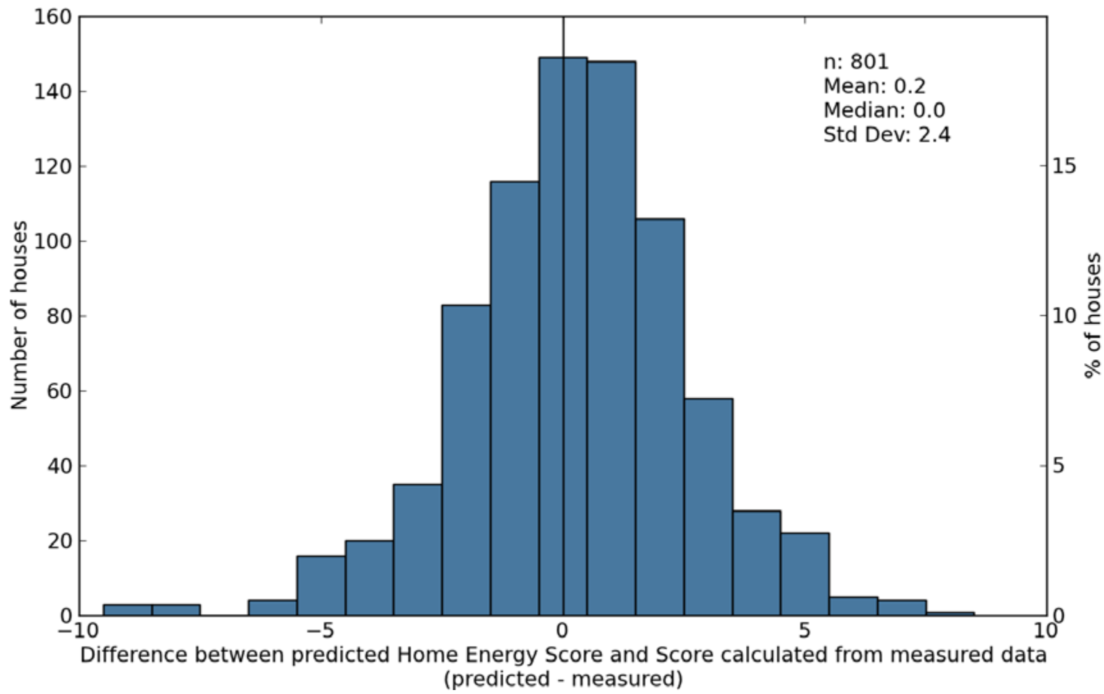

Figure 32. Histogram of differences between predicted score and score calculated from measured energy use

6.3 Sensitivity of Score to Assessment of Whole-House Leakage

Figure 33 shows the frequency distribution of the score for 655 homes in the Home Energy Score Pilot using the three variations in whole-house leakage input:

- Using the blower door data
- Using the qualitative assessment of "sealed"
- Using the qualitative assessment of "unsealed."

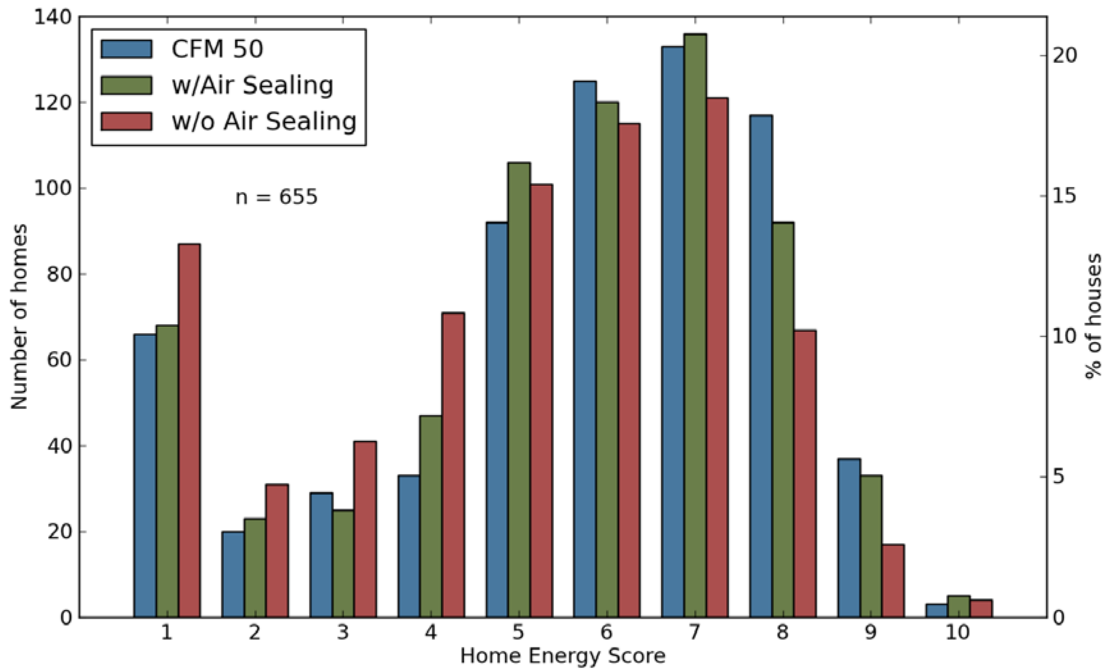

Figure 33. Distribution of Home Energy Score for 655 homes generated using three input values for whole-house leakage

Table 13 shows the average value of the Home Energy Score for each of the three whole-house infiltration modes. Note that the average score is higher using the measured whole-house leakage than for either of the qualitative input values. It appears that on average the measured air leakage for the homes in this sample is slightly lower than the default leakage estimated by HEST.

Table 13. Average Home Energy Score for Each of Three Input Scenarios for Whole-House Infiltration

	CFM50	Sealed	Unsealed
Mean Score:	5.75	5.59	5.08

Pearson's chi-square test was applied to examine the relationship between the three distributions shown in Figure 33.[27] The chi-square test tests whether the frequency distribution of observations in a sample is consistent with a historical or expected distribution. Treating the quantitative distribution as the expected distribution, and the two qualitative distributions as observed distributions, we were able to draw from chi-square tests the following statistical conclusions for this sample of homes:

- The sealed qualitative distribution is not significantly different from the quantitative distribution at a 95% CL.

[27] Scoring bins 9 and 10 were pooled together because frequencies are less than 5 (an issue with chi-square tests).

- The unsealed qualitative distribution is significantly different from the quantitative distribution at > 99% CL. Hence, we can say with confidence that using the unsealed qualitative option reduces the mean score when compared to using the quantitative input method for the set of homes considered in this analysis.

Figure 34 shows the difference in Home Energy Score generated by HEST using the quantitative and qualitative inputs for whole-house air infiltration. On average, for this sample of homes, the Home Energy Score is reduced by 0.16 points when the sealed qualitative input is used and by 0.67 points when the unsealed qualitative input is used.

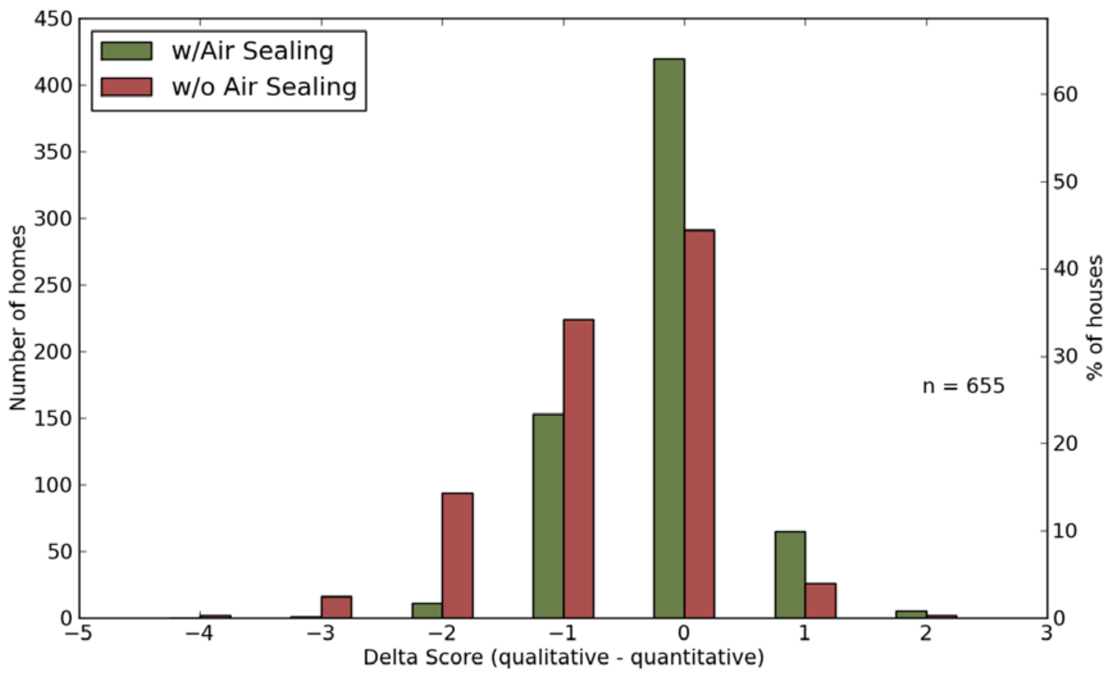

Figure 34. Distribution of differences in Home Energy Score generated using qualitative and quantitative input for whole-house leakage

An examination of the score sensitivity to the quantitative and qualitative inputs for whole-house air infiltration by climate[28] was also conducted using the pilot data. No climate-specific issues were identified by the sensitivity study.

[28] At the time of the pilot, the Home Energy Score was calculated using bins for 18 climate zones in the United States. The sensitivity study looked at variability in results across these zones.

7 References

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Appendix A Historical Progression of HEST Accuracy

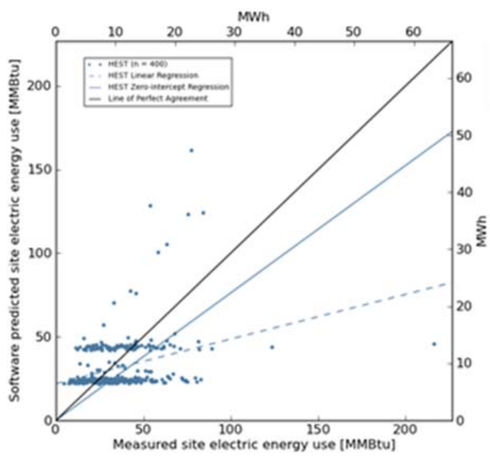
This section provides a high-level historical perspective of NREL's assessments of HEST.

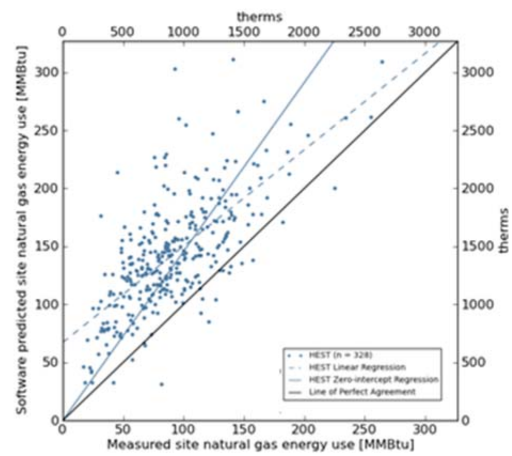
NREL first assessed the accuracy of HEST in July 2011 and provided feedback to DOE and LBNL. The final assessment reflected in this report covered the April 27, 2012 release of HEST. With each successive release of the tool, LBNL made modifications to the underlying assumptions and calculations, some in response to results generated by NREL, some driven by other factors.

Three snapshots of HEST accuracy are presented below. The data included in each assessment are different, as NREL was continually adding homes to the FDR.[29] Key modifications made to HEST between the assessments are highlighted.

A.1 July 13, 2011 Analysis

The figures and table below summarize results of HEST analysis conducted on July 13, 2011.





Date of Analysis: July 13, 2011	
Electricity	**NG**
Number of observations: 400	Number of observations: 328
Median absolute difference: 32%	Median absolute difference: 59%

At the time of this assessment HEST assumed fixed occupancy in all homes (two adults, one child), which is evident in the near-horizontal bands of the electricity use plot above. The lowest band corresponds to homes with predicted electric energy consumption of approximately 5000 kWh that use NG for space and water heating and have no space cooling. Most predicted electricity use for these homes is the HEST default electricity consumption for lighting, appliances, and MELs for two adults and one child. The horizontal band above the band at ~25 MMBtu consists of homes with electric water heating and space cooling. The points above the bands with higher predicted (and measured) electric consumption are homes with electric space heating.

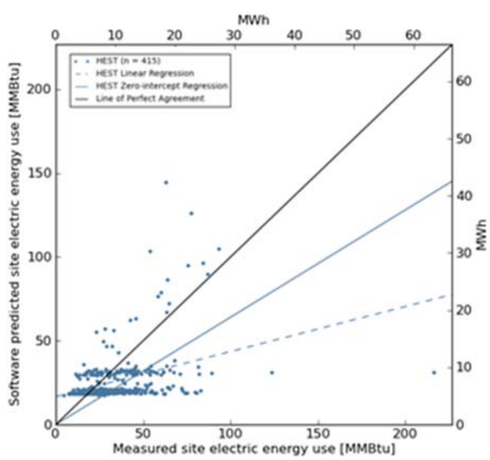
[29] Note that the scales on the graphs are not consistent across the timeline. It was not feasible to go back and adjust axes in preceding analyses as data were added to the FDR.

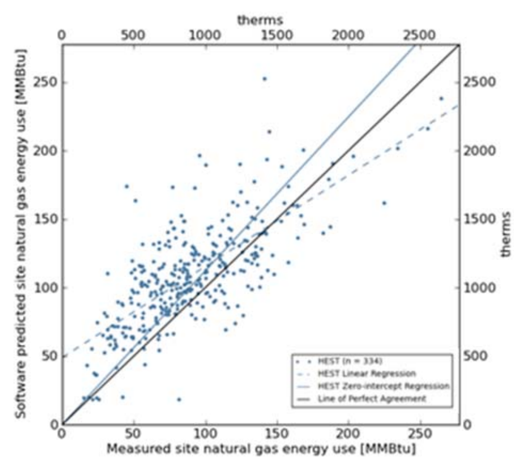
HEST also significantly overpredicted NG consumption in this version of the tool.

A.2 July 20, 2011 Analysis

Selected modifications to HEST in the July 20 update include:

- Neighboring houses on left and right assumed for shading calculations.
- Default thermostat now 78/84 cooling, 68/60 heating, compared to 78/81 and 68/64 previously.
- Default clothes washer loads now 1 warm/warm, 2 warm/cold, and 3 cold/cold per week.
- Increased DOE-2 wind shielding class, which will reduce local wind speeds.
- Conditioned basements now have thermostat setting 5 degrees lower than main living area for heating and 5 degrees higher for cooling, compared to no differential previously.
- Operable window shading now applied only during summer.
- Default refrigerator now a 10-year-old large, top freezer auto-defrost.
- Reduced default clothes dryer energy use, and number of loads to 5 per week.
- Reduced default dishwasher water use to 8.2 gallons/cycle and number of loads to 3 per week.
- Default water heater energy factors now 0.59 for gas and 0.90 for electric.
- Lowered default water heater set point to 120°F.
- Increased inlet water temperatures by approximately 8 degrees.





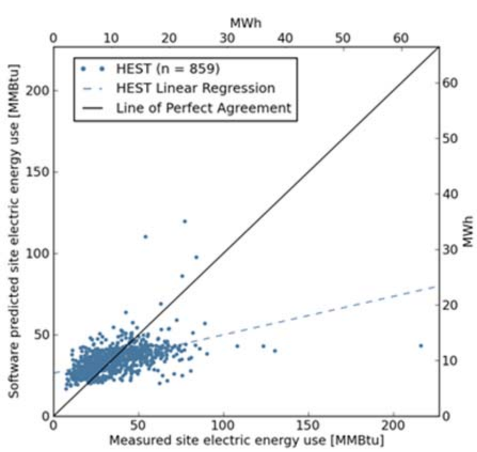
Date of Analysis: July 20, 2011	
Electricity	**NG**
Number of observations: 415	Number of observations: 334
Median absolute difference: 34%	Median absolute difference: 25%

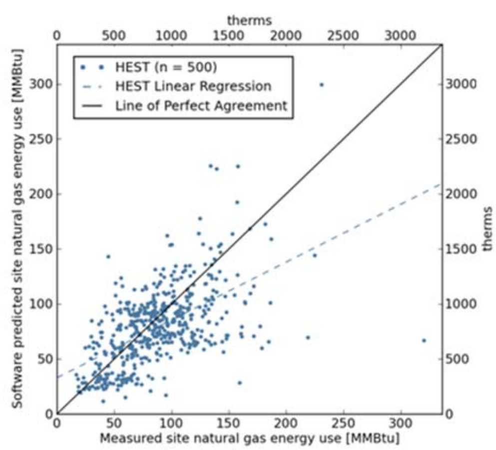
The impacts of changing set points and assumptions about basement space temperatures are evident in the NG plot and median absolute difference between predicted and measured NG use. The reduction in the hot water tank set point temperature is evident in the electricity plot; the upper band associated with hot water use is lower than in the July 13 results. However, other changes made to the software and/or data resulted in a small increase in the median absolute difference between predicted and measured electricity use.

A.3 April 27, 2012 Analysis

Selected changes made to HEST between the July 13 and April 27 analyses include:

- Updated the default for number of clothes washer loads and energy use.
- Fixed a bug where specifications for custom windows were not set correctly when all sides were the same.
- Modified occupancy so that it is no longer static, but scales with the number of bedrooms in home.
- Modified calculation of lighting energy use to be based on floor area.
- Modified calculation of appliance energy use to be based on floor area and number of bedrooms.
- Updated weather data with new average temperature and water inlet temperature values
- Updated climate zone default values for foundation type, stories above ground, window type, and dryer, stove and oven fuels.
- Updated default number of ceiling fans to "none."





Date of Analysis: April 27, 2012	
Electricity	**NG**
Number of observations: 859	Number of observations: 500
Median absolute difference: 24%	Median absolute difference: 24%

Changes made in standard occupancy assumptions had a considerable impact on the predicted electricity use, reducing the median absolute difference between predicted and measured energy use from 34% in the July 20 analysis to 24% in the April 27 analysis. The horizontal bands evident in the July 13 and July 20 electricity plots are no longer seen in the plot above; the predicted electricity use trends upward with increasing measured electric energy use.

Appendix B Use of Field Data Repository in Scoring Tool Assessment

This section describes the state and use of the FDR in the HEST assessment project.

B.1 Field Data Repository Data Collection

NREL has been working to obtain historical datasets containing robust, research-grade characteristics data coupled with utility billing data. It has proven to be a challenging process; there are many obstacles, including paucity of data and legal issues related to customer privacy. Nevertheless, NREL managed to accumulate useful data.

To start with, the FDR team focused on datasets that were available in the form of REM/Rate software input files. REM/Rate has been the most widely used home energy rating software for more than a decade, and thus REM/Rate input files are a relatively common format for existing datasets. It is used for home energy ratings (primarily supporting ENERGY STAR Qualified Homes Program), state and utility efficiency programs, and income-qualified weatherization programs. The software is used to evaluate new construction and retrofits, and its input files contain fairly detailed building characteristics. The software also has a feature that allows batch exporting of input files into a relational database. This REM/Rate database format became the starting point for the FDR.

Initial datasets that were collected and aggregated into the FDR included:

- **Oregon Energy Performance Pilot Study (Earth Advantage Institute, Conservation Services Group 2009) data.** A mix of 190 newer and older homes audited in 2008 and located in Portland and Bend.
- **Wisconsin Housing Characterization Study (Pigg and Nevius 2000) data.** Collected in 1991, a mix of 299 new and existing homes located throughout Wisconsin.
- **Houston utility study.** A sub-sample of 82 homes statistically derived from a utility program evaluation conducted by Hassel et al. in 2008 involving a sample of 226,000 homes built from 2002 through 2007.
- **Advance Energy's SystemVision homes.** Four hundred ninety high-efficiency homes receiving full home energy ratings in North Carolina and Tennessee.
- **Building America Energy Audit Assessment Housing Characterization (Nettleton and Edwards 2012) data.** One hundred twenty-five older retrofit-candidate homes receiving full home energy ratings in Minnesota and Wisconsin.
- **EPA ENERGY STAR Qualified Homes evaluation study.** Seventy-five ENERGY STAR Qualified Homes in Minnesota and Wisconsin.

These datasets resulted in a total of 1183 homes in the FDR after processing them as described in the next section.

B.2 Field Data Repository Data Processing

Housing characteristics data across these initial datasets were consistent and required no processing. The data were aggregated using REM/Rate batch database capabilities.

Utility billing data had to be processed for a subset of the datasets. To compare predicted energy use from HEST, SIMPLE, and REM/Rate to measured energy use, the utility billing data needed to be normalized for differences between the weather occurring during the utility billing period and the climate data used in the energy simulation. HEST, SIMPLE and REM/Rate use TMY2 climate data—TMY data for the 30-year period 1961–1990.

The utility billing data were weather normalized following the procedures outlined in *ASHRAE Guideline 14-2002, Annex D: Regression Techniques* (ASHRAE 2002). The requirement for 12 months of monthly billing data was waived and lowered to 10 months of billing data to increase the number of homes included in the resulting dataset. Three-parameter heating and cooling variable-base degree-day models were used, regressing monthly utility billing data against monthly degree-days calculated from coincident daily average temperatures. Historic daily average temperatures were obtained from weather stations managed by the National Climatic Data Center (NCDC)[30].

Heating models were created with NG billing data and both heating and cooling models were created with electricity billing data. For each model, goodness-of-fit criteria were established as adjusted $R^2 \geq 0.7$ for gas and adjusted $R^2 \geq 0.5$ for electricity. For cases with insufficient goodness-of-fit, the model coefficients were not used and an annual average energy use was calculated from the utility billing data. For cases with fewer than 12 months of billing data, a daily average energy use was calculated and multiplied by 365.25 to calculate an annual energy use. For cases with more than 12 months of data, the annual energy use was calculated by summing the average energy use for each calendar month. For regression models with sufficient goodness-of-fit, the model coefficients were applied to the calculated degree-days from TMY2 climate data, calculating the normalized annual consumption. Daily HDDs and CDDs for TMY2 climate data were calculated at base temperatures ranging from 40°F to 70°F. Daily average temperatures were calculated from hourly TMY2 data before use in the calculation of daily degree-days.

Utility billing data could not be obtained for the Oregon dataset, but climate-normalized annual energy uses for electricity and NG were provided by Earth Advantage Institute.

B.3 Translation of Field Data Repository Data to Software Inputs

For this project, "interpreters" were written in the Python programming language to translate FDR data to software inputs for HEST and SIMPLE. Detailed descriptions of these data translations are presented Appendix C and Appendix D.

B.4 Processing FDR Results

Results for NG and electricity use were converted to MMBtu for analysis. HEST source energy was calculated using national average site-to-source multipliers. Only homes for which successful results were returns from all three software packages and sufficient utility bills could be obtained were included in the analysis.

[30] Web url: http://www.ncdc.noaa.gov/oa/climate/stationlocator.html

Appendix C Translation of Field Data Repository Data to HEST Inputs

In translating inputs from the FDR to HEST, the goal was to provide an "out-of-the-box" set of inputs to HEST. In other words, to use HEST as close to how an assessor entering data would use it. The following is an explanation of each input to HEST and how it was derived from FDR data. The HEST input variables are identified by *italicsAndCamelCase*.

C.1 General

- *Zipcode*—The ZIP code from the house address in REM/Rate was used. For homes without a ZIP code recorded, the zip code was looked up for the city and state using postal code data from the Geonames Project.[31]
- *year*—The year the house was built.

C.2 House Shape and Size

- *houseOrientation*—In the FDR data the orientation of the windows is known. Overall house orientation is not known. House orientation was estimated by taking the side of the house with the greatest window area and assuming that it is the back of the house.
- *storiesAboveGround*— Number of above ground stories was retrieved from the FDR.
- *floorArea*—Total conditioned floor area was retrieved from the FDR.
- *ceilingHeight*—Average ceiling height was calculated by dividing the total conditioned volume by the floor area. The result was rounded to the nearest foot.

C.3 Number of Bedrooms

- *numberBedrooms*— Number of bedrooms was retrieved from the FDR.

C.4 Airtightness

- *airLeakage50ip*—The blower door measurement, measured in CFM50. If the infiltration was measured in air changes per hour at 50 Pascals (ACH50) it was converted to CFM50 using

  $$CFM50 = ACH50 \cdot Volume/60$$

  If the infiltration was measured in CFM25, it was converted to CFM50 using

  $$CFM50 = CFM25 \cdot (50/25)^{0.65}$$

- *airSealingPresent*—If the infiltration units were not measured in CFM50, CFM25, or ACH50, the infiltration measurement was omitted in HEST and the house was marked as "not air sealed," the HEST default.

[31] http://www.geonames.org

C.5 Foundation and Floor

- *foundationType*—The following mapping was used to convert foundation type from FDR to HEST compatible foundation types:

FDR Foundation Type	HEST Foundation Type
Slab	Slab-on-grade foundation
Open Crawlspace	Vented crawlspace
Enclosed Crawlspace	'Unvented Crawlspace' if the crawlspace type in REM/Rate is 'Unvented'. 'Vented Crawlspace' if the crawlspace type in REM/Rate is 'Vented' or 'Operable Vents'.
Conditioned Basement	Conditioned Basement
Unconditioned Basement	Unconditioned Basement
Conditioned Crawlspace	Unvented Crawlspace

  If the foundation type was "more than one foundation type" the foundation wall or slab with the greatest perimeter to ambient/ground was specified as the foundation type in HEST.

- *foundationSideInsulationRValue*—If the foundation type was a slab the R-value of the slab insulation with the greatest area was returned and rounded to the nearest of R-0 or R-5 (the only options for slab insulation in HEST). If the foundation type was a basement or crawlspace, the sum of the exterior, cavity, and interior rigid insulation R-values of the foundation wall with the greatest area was returned and rounded to the nearest of R-0, 11, and 19 (the only options for basement and crawlspace foundation insulation in HEST).

- *floorConstruction*—Insulation level of the floor above the basement or crawlspace. This was calculated by identifying the largest frame floor between conditioned space and the open crawlspace, enclosed crawlspace, conditioned basement, or unconditioned basement depending on the foundation type, and then adding the cavity and continuous insulation R-values and rounding to the closest of R-0, 11, 13, 15, 19, 21, 25, 30, and 38 (the only available options in HEST). Other foundation types were assumed to have zero floor insulation.

C.6 Walls

- *wallsSameAllSides*—Indicates if different wall types are described on each side of the house or if one wall type is used to describe all of the exterior walls. This input was always set to *true* to specify one wall type for the whole house.

- *wallConstructionFront*—Represents the construction of all of the walls in this case because the *wallsSameAllSides* input above was set to *true*. Wood stud walls were input with the cavity insulation rounded to the closest of the available R-values in HEST (0,3,7,11,13,15,19,21). Any continuous insulation on a wood stud wall was assumed to be 1-in. extruded polystyrene sheathing, as that was the only available option in the HEST interface. All siding on wood stud walls was assumed to be wood. Structural brick walls and concrete block walls, where applicable, were also translated accordingly. The R-values of the continuous insulation were rounded to the nearest values available in the HEST input (R-0, 5, 10 and R-0, 3, 6, respectively).

C.7 Doors and Windows

- *windowArea(Front|Back|Left|Right)*—Window area was totaled for each side and returned. For windows facing a direction between two sides (e.g., facing northeast), the window area was divided between the two sides (half area facing north, half area facing east).
- *windowUValue(Front|Back|Left|Right)*—An area-weighted average U-value was calculated for each window direction.
- *windowSolarGain(Front|Back|Left|Right)*—An area-weighted average SHGC was calculated for each window direction.
- *windowShade(Front|Back|Left|Right*—An area-weighted average interior shading factor was calculated for each window direction. A qualitative input was then selected that most closely matched the values in Table 9, p. 89, of the HEST documentation.[32]

C.8 Skylights

- *skylightsPresent*—For homes with any skylight area, this was set to "true". For homes with no skylight area, this was set to "false" and no other skylight inputs were specified.
- *skylightType*—A skylight from the HEST library was selected that most closely matched the area-weighted average U-value and SHGC of the skylights on the house.
- *skylightArea*—Total skylight area.

C.9 Attic and Roof

Only one ceiling can be specified in HEST. The ceiling with the greatest area for the house in the FDR was selected. All others were ignored.

- *atticType*—'Vaulted' ceiling in FDR was translated to a 'Cathedral Ceiling' in HEST. 'Attic' in FDR was translated to 'Unconditioned Attic' in HEST.
- *roofConstruction*—This input is a code that represents the roofing material, roof insulation (not attic floor insulation), and the presence of a radiant barrier. All roofs were assumed to have composition shingles. For roofs with vaulted ceilings, the insulation indicated in the FDR was assumed to be in the roof cavity and the nearest R-value (R-0, 11, 13, 15) available for roof insulation in HEST was selected. If a roof had a radiant barrier and no roof insulation then a radiant barrier was selected in HEST. For roofs above an unfinished attic, no insulation was specified in the *roofContruction*, but was instead specified on the attic floor in *ceilingConstruction*.
- *ceilingConstruction*—This indicates the R-value of insulation on the attic floor. For roofs above an unfinished attic, the R-value from the FDR was assumed to be on the attic floor and the nearest option for attic floor insulation in HEST was selected (R-0, 3, 9, 11, 19, 21, 25, 30, 38, 49, 60). For roofs above a vaulted ceiling, no insulation was specified in the *ceilingConstruction*.

[32] http://evanmills.lbl.gov/pubs/pdf/home-energy-saver.pdf

- *roofAbsorptivityValue*—The roof absorptivity was translated from qualitative to a quantitative value using the values in the HEST documentation:

REM/Rate Roof Color	Absorptance
Light	0.60
Medium	0.75
Dark	0.90
Reflective	0.20

C.10 Ducts and Pipes

- *ductLocation*—Duct location was translated from FDR to HEST inputs according to the following mapping:

REM/Rate Duct Location	HEST Duct Location
Open crawlspace	Vented crawlspace
Enclosed crawlspace	Unconditioned basement or unvented crawlspace
Conditioned craw space	Conditioned space
Unconditioned basement	Unconditioned basement or unvented crawlspace
Conditioned basement	Conditioned space
Attic, under insulation	Conditioned space
Attic, exposed	Unconditioned attic
Conditioned space	Conditioned space
Wall with no top plate	Unknown/not applicable
Garage	Unknown/not applicable
Exterior wall	Unknown/not applicable
Floor cavity over garage	Unknown/not applicable
Under slab floor	Conditioned space

- *ductInsulationPresent*—For homes in the FDR where the R-value of the ducts in the primary duct system was greater than R-1, the value for this input was set to "true" .
- *ductSealingPresent*—The air handler flow rate in cfm was estimated by assuming air conditioners and heat pumps in cooling mode operate at 400 cfm/ton and furnaces and heat pumps in heating mode operate at 275 cfm/ton. If necessary, the measured duct leakage was converted from CFM50 to CFM25. If the duct leakage was not measured in CFM50 or CFM25, the HEST default of "unsealed" was assumed. The measured duct leakage in CFM25 was divided by the estimated total CFM to obtain a percent leakage. For homes with CFM25 duct leakage ≤22.5% of air handler flow, the ducts were assumed to be "sealed."
- *hwFromBoiler*—For homes in the FDR where the water heating equipment that handles the largest percentage of the water heating load handles some portion of the space heating

load and is a gas or oil boiler, it was specified in HEST that the boiler provides hot water. Otherwise, it was input into HEST as having separate hot water and space heating equipment. If it was determined that the boiler provides hot water and the boiler's hot water tank volume in the FDR is greater than zero, it was specified in HEST that the boiler has an indirect tank providing hot water; otherwise, the boiler was specified as having a tankless coil to provide hot water.

C.11 Heating Equipment

For each house in the FDR, the heating system that handles the greatest percentage of the heating load was selected. All other heating equipment was ignored.

- *heatingType*—The type of primary heating equipment was translated from FDR.
- *heatingEfficiency*—The heating efficiency of the heating equipment was input from the FDR into Heating Seasonal Performance Factor (HSPF) for heat pumps and annual fuel utilization efficiency for anything else. In cases where the efficiency of a heat pump was specified in coefficient of performance (COP), it was converted to HSPF by dividing by 0.293.
- *heatingCapacity*—The heating capacity was converted from kBtu/h to Btu/h and input into HEST.

C.12 Cooling Equipment

For each home in the FDR, the mechanical equipment that handles the greatest portion of the cooling load was selected. Any other cooling equipment was ignored.

- *coolingType*—The type of cooling system. All homes in the FDR have either central air conditioning, electric heat pumps, or no air conditioning.
- *coolingEfficiency*—Seasonal Energy Efficiency Ratio (SEER) was entered for central air conditioners and heat pumps.

C.13 Water Heating

For each house in the FDR, the mechanical equipment that handles the greatest percentage of the hot water load was selected. All other hot water equipment was ignored.

- *hwFuel*—The fuel type of the primary water heater was translated from FDR.
- *hwEnergyFactor*—The energy factor of the water heater was translated from FDR.

Appendix D Translation of Field Data Repository Data to SIMPLE Inputs

In translating inputs from the FDR to SIMPLE, the goal was to provide an "out-of-the-box" set of inputs to SIMPLE. In other words, to use SIMPLE as close to how it would be used by an auditor entering data. However, in many cases the data collected were in a different form and needed to be translated. Specifically, in SIMPLE most of the inputs are qualitative in nature with numeric overrides in an override section of the spreadsheet. The FDR data are primarily numeric. To avoid introducing additional error by converting the numeric values in FDR to approximate qualitative values for input to SIMPLE, the numeric overrides were used whenever possible.

Following is an explanation of each input to SIMPLE and how it was derived from REM/Rate data.

D.1 General House Characteristics

- *Closest Weather Station*—The closest weather station was selected from the ZIP code of the house address in REM/Rate. For homes without a ZIP code recorded, the ZIP code was looked up for the city and state using postal code data from the Geonames Project.[33]
- *Finished floor area (above grd)*—For homes in the FDR with a conditioned basement, the total conditioned floor area was divided by the number of stories plus one (for the basement) to estimate the average conditioned floor area per floor. The floor area per floor was then multiplied by the number of above ground stories to estimate the finished floor area above ground.
- *Stories*—Number of above ground stories was retrieved from the FDR.
- *Bedrooms*—Number of bedrooms was retrieved from the FDR.

D.2 Heating System

- *Primary Heating Fuel*—This input describes the fuel used for the primary heating equipment. However, for electric heating it requires a selection of whether it is resistance heating, a heat pump, or a heat pump with a gas backup. For each home in the FDR, the heating system that handles the largest portion of the space-heating load was selected. The primary heating fuel was retrieved from that equipment and for electric heating equipment the appropriate equipment type was selected.
- *Heating System Type*—The heating system type is a qualitative description of the heating system efficiency. This input was overridden by the quantitative *Heating Efficiency* input.
- *Heating Efficiency (override)*—Heating efficiency was calculated for the primary heating system in the metric appropriate for the fuel type (COP for electric, annual fuel utilization efficiency for gas). For electric resistance heating, the efficiency was allowed to default in SIMPLE. Since the numeric efficiency of electric heating did not change when different qualitative efficiency inputs were selected the efficiency was assumed to be part of the logic of the SIMPLE and not intended to be an input in this case. The efficiency of air source heat pumps and dual-fuel heat pumps was converted from HSPF to COP. Then,

[33] http://www.geonames.org

a climate adjustment was applied to the COP of air source heat pumps (not dual-fuel heat pumps) according to a method recommended by Blasnik & Associates.

- *Heat Distribution Type*—The heating distribution type was selected based on the type of heating equipment (ducts for furnaces, radiators for boilers, etc.).
- *Secondary Heating Type*—This input allows the same selections as the *Primary Heating Fuel* input described above with the addition of hard and soft woods. For each home in the FDR with more than one heating system, the one that handles the second-largest portion of the space heating load was selected and translated in the same manner as the *Primary Heating* Fuel input. If the secondary heating system burns wood, 'Soft' wood was assumed and submitted to SIMPLE.
- *Secondary heating* - % home—The percentage of the heating load handled by the secondary heating system as retrieved from the FDR. If there are more than two heating systems, the primary heating system assumed the load of the third, fourth, etc. systems. For homes in the FDR with only one heating system this input was set to zero.

D.3 Walls

- *Wall Insulation*—A qualitative description of the wall insulation (e.g., "No Ins", "Partial", "Std.", "Good", "Very Good"). This input was overridden by the quantitative *Wall R* override.
- *Wall Area (override)*—Overrides the default calculated wall area within SIMPLE. The wall with the largest area between conditioned and ambient space was selected for each house in the FDR and the area of that wall was submitted.
- *Wall Area 2 (override)*—For homes in the FDR with more than one wall type between conditioned and ambient spaces, the second largest area was selected and submitted. Additional wall area between conditioned and ambient space was added to the first wall (*Wall Area* above).
- *Wall R (override)*—The assembly R-value is selected from the primary wall type for each house as determined in the *Wall Area* input above. If the wall assembly R-value from the FDR was less than R-6, the R-value was set to R-6 to replicate the "no insulation" condition in the *Wall Insulation* qualitative input.
- *Wall 2 R (override)*—The assembly R-value of the secondary wall type was calculated similarly to the *Wall R* input.

D.4 Attics

- *Attic Insulation*—A qualitative description of the attic insulation (e.g. "None", "Some", "Std. 10 inch", "High Ins"). This input was overridden by the quantitative *Attic R* override.
- *Attic Area (override)*—Overrides the default calculated attic area within SIMPLE. For each house in the FDR, the attic with the greatest area was selected as the primary attic and the area of that attic was submitted.

- *Attic Area 2 (override)*—For homes in the FDR with more than one attic type, the second largest attic area was selected and submitted. Additional attic area was attributed to the first attic (*Attic Area* above).
- *Attic R (override)*—The total R-value of the primary attic (as determined for the *Attic Area* input above) was selected from the FDR. If the attic had a calculated R-value less that R-5, the R-value was set to R-5 to replicate the "no insulation" condition in the qualitative input (*Attic Insulation*).
- *Attic 2 R (override)*—The assembly R-value of the secondary attic was calculated similarly to the *Attic R* input.

D.5 Windows

- *Window Type*—A qualitative description of the type of windows installed on the house (e.g. "Single", "Dbl/Sng&Storm", "Dbl & low e", "Super"). This is overridden by the *Windows R* override as described below.
- *Window Area*—A qualitative description of the relative amount of window area (e.g. "High", "Typical", "Low"). This is overridden by the *Windows Area* override as described below.
- *Windows Area (override)*—Square feet of window area. For each home in the FDR the window area is summed and submitted.
- *Windows R (override)*—An area-weighted average window R-value was calculated from the FDR data and submitted.

D.6 Infiltration

- *Air Tightness*—A qualitative description of the air tightness of the house (e.g. "Very Leaky", "Leaky", "Average", "Fairly Tight", "Tight", "HRV"). This is overridden by the *CFM50 Air Leakage* override as described below.
- *CFM50 Air Leakage (override)*—The qualitative airtightness input was overridden by the blower door measurement measured in CFM50. If the infiltration was measured in ACH50 it was converted to CFM50 using

  $$CFM50 = ACH50 \cdot Volume/60$$

  If the infiltration was measured in CFM25, it was converted to CFM50 using

  $$CFM50 = CFM25 \cdot (50/25)^{0.65}$$

D.7 Foundation

- *Foundation Type*—Foundation types from FDR were translated to SIMPLE according to the following mapping:

REM/Rate Foundation Type	SIMPLE Foundation Type
Slab	Slab
Open crawlspace	Crawlspace
Enclosed craw space	Crawlspace
Conditioned basement	Basement conditioned
Unconditioned basement	Basement
More than one type	Varies, see below
Apartment above conditioned space	Throws an error
Conditioned crawlspace	Crawlspace conditioned

Where there was more than one foundation type, the foundation type was determined from the foundation wall or slab with the greatest perimeter adjacent to outdoors.

- *Foundation Insulation*—A qualitative input describing the location of the foundation insulation (e.g. “None”, “Walls”, “Ceiling”). If the foundation type was a slab, “None” was assumed for foundation insulation. Otherwise, the R-values of the largest frame floor area recorded and the largest foundation wall area were compared and the one with the larger R-value was assumed to be insulated.

D.8 Ducts

- *Ducts: % in Attic*—The percentage of the supply ducts in the attic from the FDR were summed and entered into SIMPLE.
- *Ducts: % in Basement*—The percentage of supply ducts in the basement was similarly calculated.
- *Duct Insulation*—Area weighted average duct insulation R-value was calculated and then the duct insulation level available in SIMPLE closest to that R-value was selected.
- *Duct Leakiness*—Duct leakage in CFM25 was calculated for each duct and averaged by floor area served. Duct leakage measured in CFM50 was converted to CFM25 using

$$CFM25 = CFM50 \cdot (25/50)^{0.65}$$

Total air handler CFM was estimated at 400 CFM/ton for an air conditioners and heat pumps in cooling mode or 275 CFM/ton for furnaces and heat pumps in heating mode. Blasnik & Associates indicated (Blasnik 2011) that the qualitative inputs for duct leakage corresponded to the following CFM25 values for a 1200 CFM air handler:

Duct Leakage Description	CFM25 Leakage for a 1200 CFM Air Handler
Very Leaky	700
Leaky	500
Average	300
Tight	100
Airtight	0

Those values were then scaled to the approximated size of air handler. The qualitative duct leakage with the scaled value closest to the averaged CFM25 was entered into SIMPLE.

D.9 Cooling

For homes in the FDR with multiple central air, air-source heat pump, or dual-fuel heat pump systems, the equipment that handles the greatest percentage of the cooling load was assumed to be the only cooling system.

- *AC SEER*—For each home in the FDR, the efficiency of the primary air conditioning system, measured in SEER, was submitted to SIMPLE. If the efficiency was recorded in EER it was converted to SEER using the following equation from the *Building America House Simulation Protocols* (Hendron and Engebrecht 2010):

$$EER = -0.02 \times SEER^2 + 1.12 \times SEER$$

- *Window Shading*—Shading was calculated based on data from the FDR by taking the average of the summer and winter internal shading coefficients multiplied by the average of the summer and winter external shading coefficients for each window. Then, the overall shading coefficient was calculated as the area-weighted average of the shading coefficients of each window. A shading choice was then selected from the list in SIMPLE based on which choice corresponded most closely to the calculated shading coefficient.
- *Cool Roof / Rad. Barrier rafters*—A quantitative input describing the absorptivity of the roof (e.g. “Std Color”, “Reflective / low gain”, “Very Reflective”). For each home in the FDR, the absorptivity of the largest roof was used to select the option that corresponded most closely in SIMPLE. If the roof was marked as having a radiant barrier in the FDR, the input was then changed to ‘Very Reflective’, as per guidance from Blasnik & Associates (Blasnik 2011).

D.10 Water Heating

- *Water Heater Fuel*—For each house in the FDR, the water heating system that covers the largest percentage of the hot water load was used to determine the fuel type for input into SIMPLE.
- *Water Heater Type*—For each house in the FDR, the water heating system that covers the largest percentage of the hot water load was used to determine the type of water heater installed (e.g. “Standard”, “Tankless”, “High Efficiency”, “Indirect”, “Integrated”, “Heat Pump”). For conventional tank water heaters, the water heater was assumed to be ‘High

Efficiency' if the energy factor was greater than 0.9 and the fuel was not electricity (Blasnik 2011). Otherwise, the water heater was assumed to be 'Standard.' Other translations of the FDR water heater types were fairly straightforward (e.g., 'Instant' translates to 'Tankless').

- *Hot Water Fixture Efficiency*—Assumed to be *Average*.

D.11 All Else Information[34]

- *Lighting Efficiency*—Assumed to be "Average".
- *Primary Refrigerator*—For homes in the FDR where a default refrigerator was specified, an 'Average' refrigerator was selected in SIMPLE.
- *Refrigeration (override)*—Specifies kilowatt-hours per year of refrigerator energy use and overrides the *Primary Refrigerator* input above. For homes in the FDR where a user-defined refrigerator was specified, the refrigerator data were available in terms of total kWh/yr of refrigerator energy use (adding the energy use of more than one refrigerator, if necessary). Those data were then used here to override the *Primary Refrigerator* input.
- *Extra Refrigerators / Freezers*—Assumed to be "None".
- *Entertainment (TVs & PCs)*—Assumed to be "Average".
- *# Other Large Uses (500 kWh)*—Number of other electricity uses near 500 kWh/yr. Assumed to be zero.
- *Other Plug Loads*—Assumed to be "Average".
- *Clothes Dryer Fuel*—Retrieved from the FDR for each house.
- *Cooking Fuel*—Retrieved from the FDR for each house.

D.12 Occupancy and Behavior

- *Occupants*—Set to zero, which caused SIMPLE to make a default assumption about occupancy based on other inputs.
- *Heating Setpoint*—The average heating setpoint was selected to match the average of the heating set point schedule[35] in HEST: 65°F.
- *Cooling Setpoint*—The average cooling setpoint was selected to match the average of the cooling set point schedule[36] in HEST: 80.25°Ft.

[34] *All Else Information* is SIMPLE terminology.
[35] http://goo.gl/SaRof
[36] http://goo.gl/SaRof

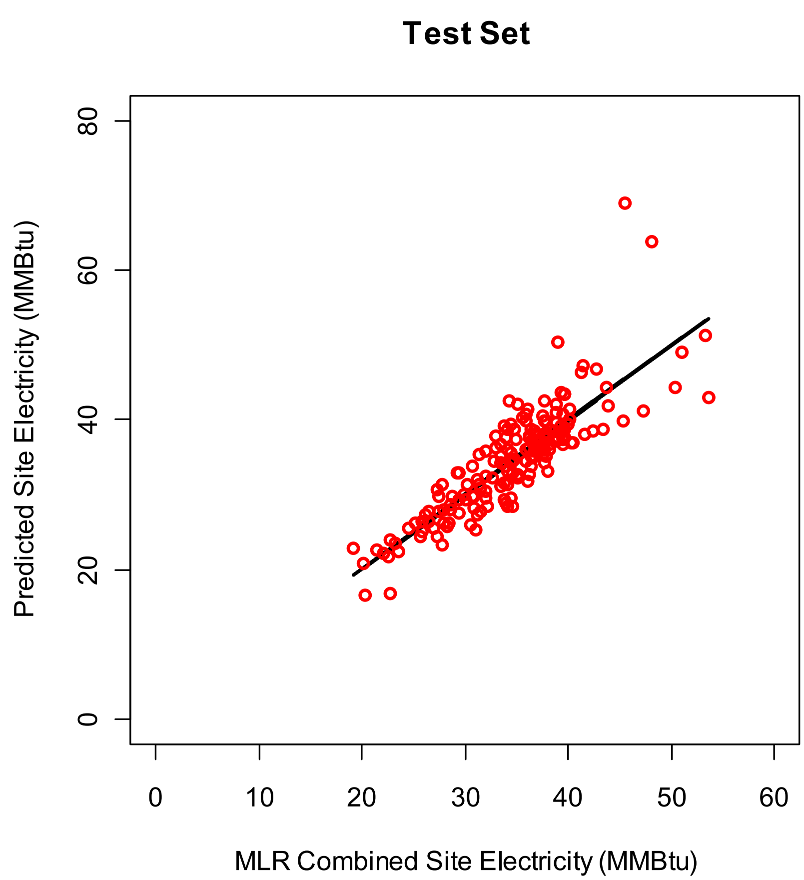
Appendix E Additional Statistical Model Information

Included in this appendix are additional information and background materials for the statistical models developed in Section 3. Additional validations of the difference models are provided. A complete list of coded variables and descriptions are included.

E.1 Additional Validation of MLR models

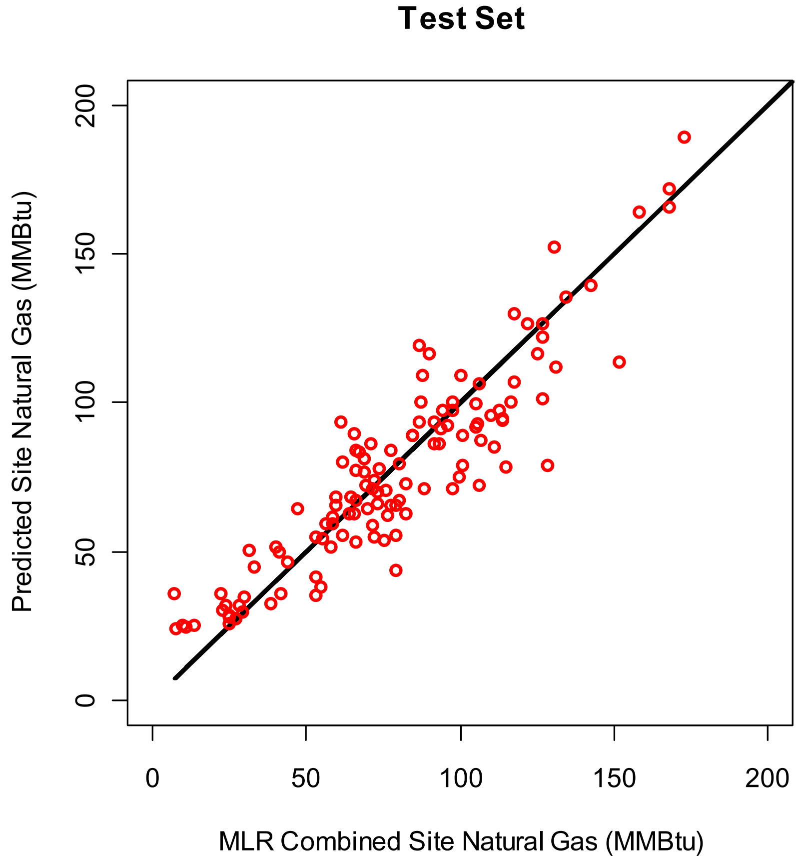
In Section 3, measured energy use and differences (predicted minus measured) in energy use were modeled separately for each energy type. Because the models of differences had very low R-squared values, an additional validation was done. By adding the MLR prediction for differences to the MLR prediction for measured, an MLR prediction of the HEST prediction is obtained. Hence, a simple linear regression can be applied for HEST prediction as a function of this combined MLR prediction.

The figure below shows the HEST prediction versus the MLR prediction for site electricity use. The data shown are from the test set. The adjusted R-squared was 0.723, which can be interpreted that the MLR models can recover approximately 72% of the HEST prediction.



HEST prediction versus combined MLR models for measured site electricity

The figure below shows the HEST prediction versus the MLR prediction for site NG usage. Again, the data shown are from the test set. The adjusted R-squared was 0.861, which means the MLR models recover approximately 86% of the HEST prediction.



MLR HEST prediction versus combined MLR models for measured site NG

E.2 Home Energy Score Test Variables Tested in Statistical Analysis

This section lists the HEST variables and coding used for the statistical analysis. In addition to inputs listed in Appendix C, base 65°F HDDs, base 65°F CDDs, and a few combined variables were included in the analysis. The table below gives a complete list of HEST variables and descriptions.

Variables Used for Statistical Analysis and Descriptions

Number	Coded Variable	Original Variables and Inputs	Original Variable Description
1	C_HDD_65F	HDD_65F	HDDs (base 65°F)
2	C_CDD_65F	CDD_65F	CDDs (base 65°F)
3	C_numberBedrooms	numberBedrooms	Number of bedrooms
4	C_storiesAboveGround	storiesAboveGround	Stories above ground level
5	C_ceilingHeight	ceilingHeight	Ceiling height (feet)

Number	Coded Variable	Original Variables and Inputs	Original Variable Description
6	C_floorArea	floorArea	Floor area (ft^2)
7	C_houseOrientation	houseOrientation	House orientation degrees (north = 0, east = 90, south = 180, and west = 270)
8	C_airLeakage50ip	airLeakage50ip	Air Leakage (cubic feet per minute)
9	C_roofAbsorptance	roofAbsorptance	Roof absorptance
10	C_fndtnInsulRValue	foundation-SideInsulationRValue	Foundation side insulation R-value
11	C_skylightArea	skylightArea	Skylight area (ft^2)
12	C_windowAreaTotal	windowArea	Window area total
13	C_WAU_Total	windowArea*U	sum((Window area) × (U-factors))
14	C_WASG_Total	windowArea*SHGC	sum((Window area) × (SHGC))
15	C_N_windowArea	windowAreaFront, windowAreaRight, windowAreaBack, and windowAreaLeft	Direction of window area determined from houseOrientation
16	C_E_windowArea	same as above	same as above
17	C_S_windowArea	same as above	same as above
18	C_W_windowArea	same as above	same as above
19	C_N_WAU	Directional windowArea*U	(Window area) × (U-factors)
20	C_E_WAU	same as above	same as above
21	C_S_WAU	sames as above	same as above
22	C_W_WAU	same as above	sames as above
23	C_N_WASG	Directional windowArea*SHGC	(Window area) × (SHGC)
24	C_E_WASG	sames as above	same as above
25	C_S_WASG	same as above	same as above
26	C_W_WASG	same as above	same as above
27	C_heatingEfficiency	heatingEfficiency	System heating efficiency
28	C_coolingEfficiency	coolingEfficiency	Cooling efficiency for air conditioner
29	C_hwFuel	hwFuel	Hot water fuel type (gas or electric)
30	C_hwEnergyFactor	hwEnergyFactor	Hot water energy factor
31	C_RoofRValue	roofRValue	Roof R-value determined from roof construction and ceiling construction inputs
32	C_FloorRValue	floorRValue	Floor R-value determined from floor construction input
33	C_WallRValue	wallRValue	Wall R-value determined from wall construction input
34	Bend_OR	Bend, OR	Bend, Oregon in climate zone 18
35	Built_2001_plus	from yearBuilt	House built in 2001 or later
36	Built_1976_to_2000		House built between 1976 and 2000

Number	Coded Variable	Original Variables and Inputs	Original Variable Description
37	Built_1951_to_1975		House built between 1951 and 1975
38	C_HT_GBL	heatingType	Heating type GBL (gas boiler)
39	C_HT_GWF		Heating type GWF (gas wall furnace)
40	C_HT_EBB		Heating type EBB (electric baseboard)
41	C_HT_EFN		Heating type EFN (electric furnace)
42	C_HT_EHP		Heating type EHP (electric heat pump)
43	C_RC_rfps11co	roofConstruction	Roof construction code rfps11co
44	C_RC_rfps15co		Roof construction code rfps15co
45	C_RC_rfrb00co		Roof construction code rfrb00co
46	C_RC_rfwf00co		Roof construction code rfwf00co
47	C_RC_rfwf11co		Roof construction code rfwf11co
48	C_RC_rfwf15co		Roof construction code rfwf15co
49	C_AT_cath_ceil	atticType	Attic type of cathedral ceiling
50	C_CC_ecwf00	ceilingConstruction	Ceiling construction code ecwf00
51	C_CC_ecwf03		Ceiling construction code ecwf03
52	C_CC_ecwf06		Ceiling construction code ecwf06
53	C_CC_ecwf09		Ceiling construction code ecwf09
54	C_CC_ecwf19		Ceiling construction code ecwf19
55	C_CC_ecwf21		Ceiling construction code ecwf21
56	C_CC_ecwf25		Ceiling construction code ecwf25
57	C_CC_ecwf30		Ceiling construction code ecwf30
58	C_CC_ecwf38		Ceiling construction code ecwf38
59	C_FT_slab	foundationType	Foundation type code slab
60	C_FT_uncond_base		Foundation type code uncond_base
61	C_FT_unvent_crawl		Foundation type code unvent_crawl
62	C_FT_vent_crawl		Foundation type code vent_crawl
63	C_FC_efwf00ca	floorConstruction	Floor construction code efwf00ca
64	C_FC_efwf11ca		Floor construction code efwf11ca
65	C_FC_efwf13ca		Floor construction code efwf13ca
66	C_FC_efwf15ca		Floor construction code efwf15ca
67	C_FC_efwf19ca		Floor construction code efwf19ca
68	C_FC_efwf21ca		Floor construction code efwf21ca
69	C_FC_efwf25ca		Floor construction code efwf25ca
70	C_FC_efwf30ca		Floor construction code efwf30ca
71	C_FC_efwf38ca		Floor construction code efwf38ca
72	C_WC_ewps00wo	wallConstruction	Wall construction code ewps00wo
73	C_WC_ewps03wo		Wall construction code ewps03wo
74	C_WC_ewps11wo		Wall construction code ewps11wo
75	C_WC_ewps13wo		Wall construction code ewps13wo
76	C_WC_ewps15wo		Wall construction code ewps15wo

Number	Coded Variable	Original Variables and Inputs	Original Variable Description
77	C_WC_ewps19wo		Wall construction code ewps19wo
78	C_WC_ewps21wo		Wall construction code ewps21wo
79	C_WC_ewwf00br		Wall construction code ewwf00br
80	C_WC_ewwf00wo		Wall construction code ewwf00wo
81	C_WC_ewwf03wo		Wall construction code ewwf03wo
82	C_WC_ewwf07wo		Wall construction code ewwf07wo
83	C_WC_ewwf13wo		Wall construction code ewwf13wo
84	C_WC_ewwf15wo		Wall construction code ewwf15wo
85	C_WC_ewwf19wo		Wall construction code ewwf19wo
86	C_WC_ewwf21wo		Wall construction code ewwf21wo
87	C_ST_dcab	skylightType	Skylight type dcab (double pane clear, aluminum frame)
88	C_ST_dcaw		Skylight type dcaw (double pane clear, wood or vinyl frame)
89	C_ST_dpeaab		Skylight type dpeaab (double pane, low e, argon gas fill, ATB frame)
90	C_ST_dpeaaw		Skylight type dpeaaw (double pane, low e, argon gas fill, wood or vinyl frame)
91	C_ST_dseab		Skylight type dseab (double pane, low e, ATB frame)
92	C_ST_dseaw		Skylight type dseaw (double pane, low e, wood or vinyl frame)
93	C_ST_thmabw		Skylight type thmabw (triple pane, low e, argon gas fill, wood or vinyl frame)
94	C_CT_cac	coolingType	Cooling type cac (central air conditioning)
95	C_CT_ehp		Cooling type ehp (electric heat pump)
96	C_DL_uncond_attic	ductLocation	Duct location uncond_attic
97	C_DL_uncond_base		Duct location uncond_base
98	C_HWB_separate	hwFromBoiler	Hot water boiler (highly correlated with C_HT_GBL
99	C_HWB_tankless	hwTankless	Hot water tankless heater

The table below gives details on the coding used. As mentioned in Section 4.2, some inputs like floor area are numeric, but many of the inputs use DOE-2 codes to describe various types of building construction components (tables for these codes can be found at https://sites.google.com/a/lbl.gov/hes-public/calculation-methodology/appendices/appendix-e). There are separate codes for skylight types, wall types, roof types, foundation types, and many other components that make up a building. The "NG" column in the table indicates that the variable was tested in the NG models. The "Electricity" column in the table indicates that the variable was tested in electricity models.

Coding Details for Variables Used for Statistical Analysis.

Number	Coded Variable	Variable Type	Coding	Control for Binary	NG	Elec-tricity
1	C_HDD_65F	Numeric	Univariate	Not applicable	x	x
2	C_CDD_65F	Numeric	Univariate	Not applicable	x	x
3	C_numberBedrooms	Numeric	Univariate	Not applicable	x	x
4	C_storiesAboveGround	Numeric	Univariate	Not applicable	x	x
5	C_ceilingHeight	Numeric	Univariate	Not applicable	x	x
6	C_floorArea	Numeric	Univariate	Not applicable	x	x
7	C_houseOrientation	Numeric	Univariate	Not applicable	x	x
8	C_airLeakage50ip	Numeric	Univariate	Not applicable	x	x
9	C_roofAbsorptance	Numeric	Univariate	Not applicable	x	x
10	C_fndtnInsulRValue	Numeric	95th percentile = 1, zero = -1	Not applicable	x	x
11	C_skylightArea	Numeric	95th percentile = 1, zero = -1	Not applicable	x	x
12	C_windowAreaTotal	Numeric	Univariate	Not applicable	x	x
13	C_WAU_Total	Numeric	Univariate	Not applicable	x	x
14	C_WASG_Total	Numeric	Univariate	Not applicable	x	x
15	C_N_windowArea	Numeric	Univariate	Not applicable	x	x
16	C_E_windowArea	Numeric	Univariate	Not applicable	x	x
17	C_S_windowArea	Numeric	Univariate	Not applicable	x	x
18	C_W_windowArea	Numeric	Univariate	Not applicable	x	x
19	C_N_WAU	Numeric	95th percentile = 1, zero = -1	Not applicable	x	x
20	C_E_WAU	Numeric	Univariate	Not applicable	x	x
21	C_S_WAU	Numeric	Univariate	Not applicable	x	x
22	C_W_WAU	Numeric	Univariate	Not applicable	x	x
23	C_N_WASG	Numeric	Univariate	Not applicable	x	x
24	C_E_WASG	Numeric	Univariate	Not applicable	x	x
25	C_S_WASG	Numeric	Univariate	Not applicable	x	x

Number	Coded Variable	Variable Type	Coding	Control for Binary	NG	Elec-tricity
26	C_W_WASG	Numeric	Univariate	Not applicable	x	x
27	C_heatingEfficiency	Numeric	Univariate	Not applicable	x	x
28	C_coolingEfficiency	Numeric	Univariate	Not applicable		x
29	C_hwFuel	Binary	Gas = 1, Electric = -1	Not applicable	x	x
30	C_hwEnergyFactor	Numeric	Modified univariate	Not applicable	x	x
31	C_RoofRValue	Numeric	Univariate	Not applicable	x	x
32	C_FloorRValue	Numeric	95th percentile = 1, zero = -1	Not applicable	x	x
33	C_WallRValue	Numeric	Univariate	Not applicable	x	x
34	Bend_OR	Binary	Yes = 1, No = 0	Not Bend	x	x
35	Built_2001_plus	Binary	Yes = 1, No = 0	1800 to 1950	x	x
36	Built_1976_to_2000	Binary	Yes = 1, No = 0	1800 to 1950	x	x
37	Built_1951_to_1975	Binary	Yes = 1, No = 0	1800 to 1950	x	x
38	C_HT_GBL	Binary	Yes = 1, No = 0	HT = GFN	x	x
39	C_HT_GWF	Binary	Yes = 1, No = 0	HT = GFN	x	x
40	C_HT_EBB	Binary	Yes = 1, No = 0	HT = GFN		x
41	C_HT_EFN	Binary	Yes = 1, No = 0	HT = GFN		x
42	C_HT_EHP	Binary	Yes = 1, No = 0	HT = GFN		x
43	C_RC_rfps11co	Binary	Yes = 1, No = 0	RC = rfps00co	x	x
44	C_RC_rfps15co	Binary	Yes = 1, No = 0	RC = rfps00co	x	x
45	C_RC_rfrb00co	Binary	Yes = 1, No = 0	RC = rfps00co	x	x
46	C_RC_rfwf00co	Binary	Yes = 1, No = 0	RC = rfps00co	x	x
47	C_RC_rfwf11co	Binary	Yes = 1, No = 0	RC = rfps00co	x	x
48	C_RC_rfwf15co	Binary	Yes = 1, No = 0	RC = rfps00co	x	x
49	C_AT_cath_ceil	Binary	Yes = 1, No = 0	AT = uncond_attic	x	x
50	C_CC_ecwf00	Binary	Yes = 1, No = 0	CC = ecwf11	x	x
51	C_CC_ecwf03	Binary	Yes = 1, No = 0	CC = ecwf11	x	x
52	C_CC_ecwf06	Binary	Yes = 1, No = 0	CC = ecwf11	x	x
53	C_CC_ecwf09	Binary	Yes = 1, No = 0	CC = ecwf11	x	x
54	C_CC_ecwf19	Binary	Yes = 1, No = 0	CC = ecwf11	x	x
55	C_CC_ecwf21	Binary	Yes = 1, No = 0	CC = ecwf11	x	x
56	C_CC_ecwf25	Binary	Yes = 1, No = 0	CC = ecwf11	x	x
57	C_CC_ecwf30	Binary	Yes = 1, No = 0	CC = ecwf11	x	x

Number	Coded Variable	Variable Type	Coding	Control for Binary	NG	Elec-tricity
58	C_CC_ecwf38	Binary	Yes = 1, No = 0	CC = ecwf11	x	x
59	C_FT_slab	Binary	Yes = 1, No = 0	FT = cond_base	x	x
60	C_FT_uncond_base	Binary	Yes = 1, No = 0	FT = cond_base	x	x
61	C_FT_unvent_crawl	Binary	Yes = 1, No = 0	FT = cond_base	x	x
62	C_FT_vent_crawl	Binary	Yes = 1, No = 0	FT = cond_base	x	x
63	C_FC_efwf00ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
64	C_FC_efwf11ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
65	C_FC_efwf13ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
66	C_FC_efwf15ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
67	C_FC_efwf19ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
68	C_FC_efwf21ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
69	C_FC_efwf25ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
70	C_FC_efwf30ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
71	C_FC_efwf38ca	Binary	Yes = 1, No = 0	FC = (blank)	x	x
72	C_WC_ewps00wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
73	C_WC_ewps03wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
74	C_WC_ewps11wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
75	C_WC_ewps13wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
76	C_WC_ewps15wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
77	C_WC_ewps19wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
78	C_WC_ewps21wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
79	C_WC_ewwf00br	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
80	C_WC_ewwf00wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
81	C_WC_ewwf03wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
82	C_WC_ewwf07wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
83	C_WC_ewwf13wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
84	C_WC_ewwf15wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
85	C_WC_ewwf19wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x
86	C_WC_ewwf21wo	Binary	Yes = 1, No = 0	WC = ewwf11wo	x	x

Number	Coded Variable	Variable Type	Coding	Control for Binary	NG	Elec-tricity
87	C_ST_dcab	Binary	Yes = 1, No = 0	No skylight	x	x
88	C_ST_dcaw	Binary	Yes = 1, No = 0	No skylight	x	x
89	C_ST_dpeaab	Binary	Yes = 1, No = 0	No skylight	x	x
90	C_ST_dpeaaw	Binary	Yes = 1, No = 0	No skylight	x	x
91	C_ST_dseab	Binary	Yes = 1, No = 0	No skylight	x	x
92	C_ST_dseaw	Binary	Yes = 1, No = 0	No skylight	x	x
93	C_ST_thmabw	Binary	Yes = 1, No = 0	No skylight	x	x
94	C_CT_cac	Binary	Yes = 1, No = 0	No AC	x	x
95	C_CT_ehp	Binary	Yes = 1, No = 0	No AC		x
96	C_DL_uncond_attic	Binary	Yes = 1, No = 0	DL = cond_base	x	x
97	C_DL_uncond_base	Binary	Yes = 1, No = 0	DL = cond_base	x	x
98	C_HWB_separate	Binary	Yes = 1, No = 0	HWB = (blank)		x
99	C_HWB_tankless	Binary	Yes = 1, No = 0	HWB = (blank)		x

Appendix F Statistical Equations

The table below shows the mathematical equations used to populate Table 1 and Table 2 in Section 2.

Statistic	Description	Equation
Number of Observations	The number of observations in sample	n
Mean Measured	The mean value of the measured observations	$\frac{\sum_{i=1}^{n} m_i}{n}$
Mean Predicted	The mean value of the predicted observations	$\frac{\sum_{i=1}^{n} p_i}{n}$
Difference	Differences between predicted and measured observations (d)	$p - m$
Mean Difference	The mean value of the differences between predicted and measured observations ($\bar{d}$)	$\frac{\sum_{i=1}^{n}(p_i - m_i)}{n}$
Median Difference	The median value of the differences between predicted and measured observations	The value for which 50% of errors are lower and 50% are higher.
Standard Deviation of Difference	The sample standard deviation of the differences	$\sqrt{\frac{1}{n-1}\sum_{i-1}^{n}(d_i - \bar{d})^2}$
Mean Absolute Difference	The mean value of the absolute differences	$\frac{\sum_{i=1}^{n}\lvert d_i \rvert}{n}$
Median Absolute Difference	The median value of the absolute differences	The value for which 50% of errors are lower and 50% are higher.
Mean Absolute Percent Difference	The mean value of the absolute differences	$\frac{\sum_{i=1}^{n}\left\lvert {d_i}/{m_i} \right\rvert}{n}$
Median Absolute Percent Difference	The median value of the absolute differences	The value for which 50% of errors are lower and 50% are higher.
Root Mean Squared Error (RMSE)	The square root of the mean value of the squared differences	$RMSE = \sqrt{\frac{\sum_{i=1}^{n} {d_i}^2}{n}}$
Percent Root Mean Square Error	Normalized square root of the mean value of the squared differences	$NRMSE = \frac{RMSE \times 100}{Mean\ Measured}$